University of West Bohemia in Pilsen

Faculty of Applied science

Department of Cybernetics

Diploma thesis

Rotating machines diagnostics with use of LabView

Plzen 2013 Karel Kalista

Statement

I hereby submit for review and defense the diploma thesis, prepared at the end of study at the Faculty of Applied Science University of West Bohemia. I declare that I prepared this diploma thesis independently, using professional literature and resources listed in the list, which is part of this thesis. I also declare that all the software used to solve this thesis is legal.

In Pilsen, on May 18, 2013

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Acknowledgement

I would like to express my sincere appreciation to my supervisor, Ing. Jindřich Liška, Ph.D., for his support, care, encouragement and enthusiastic supervision throughout my study. His extensive discussions around my work and interesting explorations helps me to resolve problems which seemed to be insuperable.Under his guidance, I have gained not only valuable knowledge but also the logical way of thinking to deal with problems effectively.

I am very grateful to Ing. Ingrid Hochmannová who gave me many relevant references and also provided experimental data and communication with the submitter Areva GmbH.

My thanks are also due to Dr.-Ing. Francis Fomi Wamba, as a representative member of the submitter, who discussed the submission and brought relevant suggestions and comments to the final application implemented in LabView.

I would like to thank to my colleague and friend Ing. Miroslav Jiřík who helped me to understand some issues concerning clustering and classification.

I am indebted, forever, to my parents and brother, for their understanding, unconditional love and endless encouragement.

Anotace

Práce pojednává o diagnostice rotačních strojů, jmenovitě o větrných elektrárnách. Práce přináší informace o uspořádání offshore větrných elektrárnách, které jsou umístěné na větrné farmě Alpha Ventus. Dále je objasněn význam údržby na základě sledování stavu zařízení a také obecná struktura monitorovacích systémů. V práci je také uvedeno několik nejvýznamnějších typů poruch spolu se symptomy, kterými se projevují.
Druhá část práce popisuje proces zpracování dat s důrazem na získání charakteristických parametrů z vibračních dat a jejich následnou redukci pouze na ty nejvíce relevantní. Na základě uvedených poznatků byl navržen způsob, jak poruchy diagnostikovat.
V praktické části jsou popsány experimentální vibrační data a je uvedena případová studie. Dále je na datech otestován navržený postup pro diagnostiku poruch. Na závěr je uveden návod k aplikaci vytvořené v LabView, pomocí které bylo možné data analyzovat.

Klíčová slova

údržba na základě sledování stavu, monitorovací systémy stavu, poruchy rotačních strojů, Fourierova transformace, redukce příznaků, detekce poruch, klasifikace

Abstract

Presented work deals with rotating machines diagnostics, namely wind turbines. The paper provides information about the configuration of specific offshore wind turbines placed in the wind farm Alpha Ventus. Further, the meaning of condition-based maintenance is explained and the general structure of health monitoring system is described as well as the most common faults in conjunction with their symptoms.
The following part explains the data processing with a view to feature extraction from vibration data and feature reduction to identify the most relevant ones. Based on introduced knowledge, a technique for fault diagnostics is suggested.
In the practical part, the experimental vibration data are examined and a case study based on real data is presented and the proposed diagnostic approach is tested. Finally, a guide to the application implemented in LabView, which provided the data analysis, is introduced.

Keywords

condition-based maintenance, health monitoring system, rotating machines faults, vibration, Fourier transform, feature reduction, fault detection, pattern classification

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Acronyms

HMS Health Monitoring System

CBM Condition Based Maintenance

MW Megawatt

DFT Discrete Fourier Transform

FFT Fast Fourier Transform

UTC Coordinated Universal Time

ISO International Standard Organisation

RMS Root Mean Square

CoM Centre of Mass

GMF Gear Mesh Frequency

RPM Revolution Per Minute

OA Order Analysis

PCA Principal Component Analysis

1 Introduction

Renewable energy is currently very popular topic, especially in relation to the global fear of nuclear energy. It helps to bring new investments and money into this branch to make it maximally effective. Currently, many wind turbines are under construction and many were already built offshore or onshore. Since the investments at the beginning are not small as well as cost of maintenance, a great demand on turbine reliability and availability exists because it is the only way to make wind power more competitive.
One of the possibilities to ensure effective turbine running is to prevent unexpected failures, which may cause long downtime and even large turbine damage. That can be provided via time monitoring of various features and subsequently an expert analysis is performed. Both these tasks are required to be carried out automatically without human interference, ideally on the turbine station. These Health Monitoring System (HMS) automatically check health condition of wind turbine and detects fault, its location or type and assess the fault severity. The diagnostics information is subsequently used in scheduling preventive maintenance or urgent one to prevent serious failure. Hence, health monitoring systems play an important role in the operation of rotating machinery, including improving safety, increasing efficiency and lifetime, and reducing downtime and total costs. Nevertheless, the mentioned benefits can be achieved only when fault diagnosis provides reliable information on machine health conditions. If incorrect diagnosis results are generated frequently, ineffective maintenance may be arranged and the health monitoring system make no sense. Therefore, it is necessary to accentuate the case analysis during own development to maximally improve the quality of fault diagnosis. This work may represent the first step just in analysing the specific situation. The configuration of a specific wind turbine is described along with vibration measurement facilities. Further, the particular faults are described in conjunction with theirs symptoms and a suggestion of fault diagnostic approach is introduced. In the practical part, the case study based on real data is described and proposed diagnostic approach is tested.

2 Background

2.1 Wind turbine

Wind turbines are energy converters. Independently of their application, type or detailed design, all wind turbines have in common that they convert the kinetic energy of the flowing air mass into mechanical energy of rotation [9].
To maximally exploit the wind energy potential of favourable locations, the wind turbines form groups also called wind farms. Such a wind farm can consist of hundreds of wind turbines and occupy area of hundreds of square kilometres onshore or offshore.

2.1.1 Alpha Ventus Wind Farm

Alpha Ventus (also known as Borkum West) is the first offshore wind farm built in Germany. It is situated in the North Sea north of the island Borkum and it was commissioned on April 27, 2010. The park consists of twelve wind turbines of which six turbines are 5 Megawatt (MW) Areva Multibrid M5000. The farm is controlled via the control centre in the town of Nordern. The rated output of the wind farm is 60 MW.
The Alpha Ventus offshore wind farm is located in the open sea with a water depth of about 30 meters and a distance from the coast of 60 kilometres. This location guarantees excellent wind condition, however, the water depths, the aggressive salt-laden air, the strong and often gusty winds and the swell together add up to extreme demands on the installation logistics, construction, operation and as well maintenance [5].

2.1.2 Areva Multibrid M5000

Multibrid M5000 is a new platform of offshore wind turbines, which was developed in AREVA Wind GmbH (basic information can be found in Appendices A). It contains all typical components such as:

- rotor (rotor blades, aerodynamic brake and hub);
- drive train (rotor shaft, bearings, brake, gearbox and generator);
- yaw system between nacelle and tower (yaw bearing and yaw drive);
- supporting structure (tower and foundation);
- electrical components for control and grid connection.

Detail description of each component can be found e.g. in [9]. In following sections, the specific information about components of Multribrid M5000 is given. Especially about components which are significant for vibration analysis or which are special.

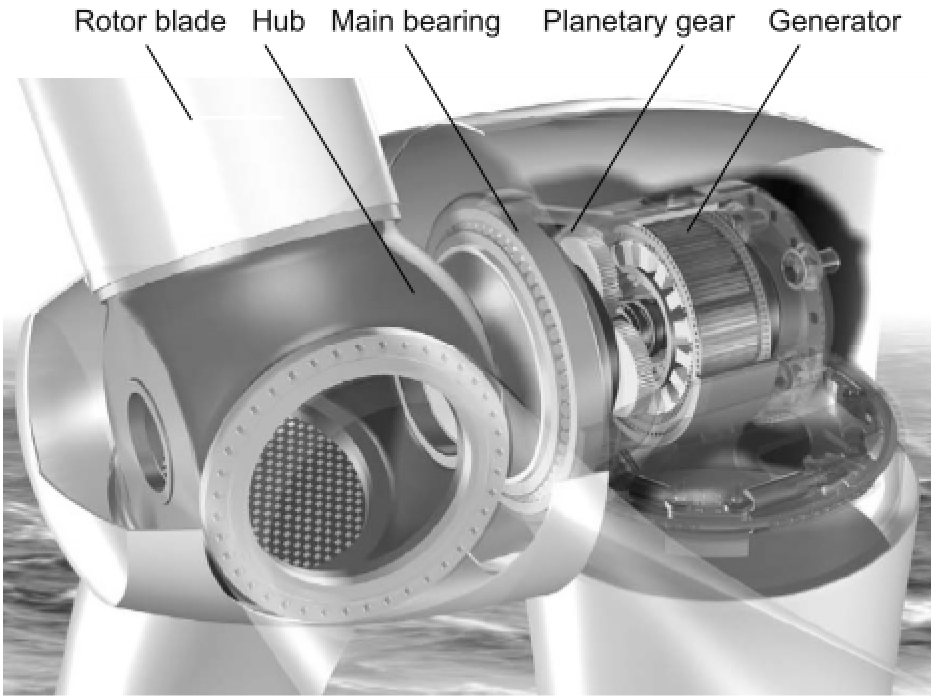


Figure 2.1.1: Multirbid M5000 [9]

2.1.2.1 Planetary gearbox

The first simple planetary gearing could be found already in ancient Greek. At present, the ancient idea was brought to perfection to obtain the best effectiveness. Main parts of planetary (epicyclic) gearbox are:

- outer ring gear;
- planet gears;
- sun (central) gear.

Planet gears are revolving about the sun gear and are usually mounted on a carrier, which is driven by input torque and itself rotates relative to the sun gear, which provides the output torque. The ring gear is fixed and meshes with the planet gears.

Planetary gearbox can by classified into:

- simple gearbox - one sun, one outer ring gear, one carrier and one planetary set;
- compound gearbox - involve more sophisticated structure involving more parts mentioned above.

In comparison with the simple planetary gearbox, the compound one reaches larger reduction ratio and higher torque-to-weight ration. Moreover, the configuration is more flexible.
In case of Multibrid M5000, the compound stepped-planet planetary gearbox shown in Figure 2.1.2 is used. This configuration is characteristic by a shaft connection between two differently-sized planet gears in each planet train. The large one engages the sun, while the small one engages the outer ring. This constitution achieves smaller step changes in gear ratio, when the overall package size is limited.

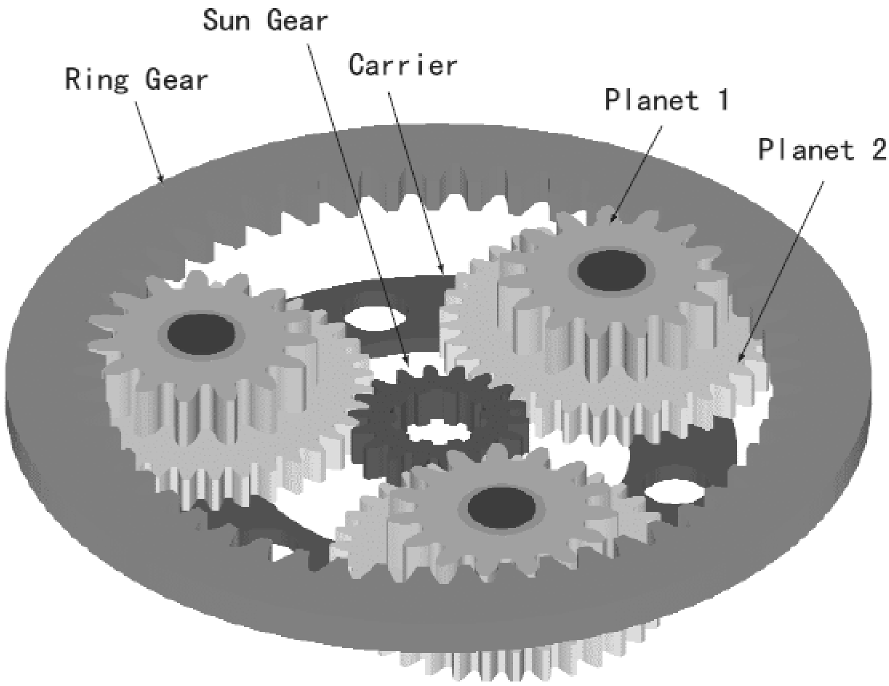


Figure 2.1.2: Typical configuration of stepped planet gear

2.1.2.2 AeroDrive

The Voith's AeroDrive is placed in the driveline of the wind turbine between the main gearbox and the generator. Its goal is to convert the changing speed in the rotor and the gearbox into a constant speed for the generator. The heart of this technology is a variable-speed hydrodynamic gearbox whose two main components are:

- planetary gear (superposition gear);
- hydrodynamic torque converter (WinDrive).

In Figure 2.1.3, the configuration of the driveline of the wind turbine is shown.

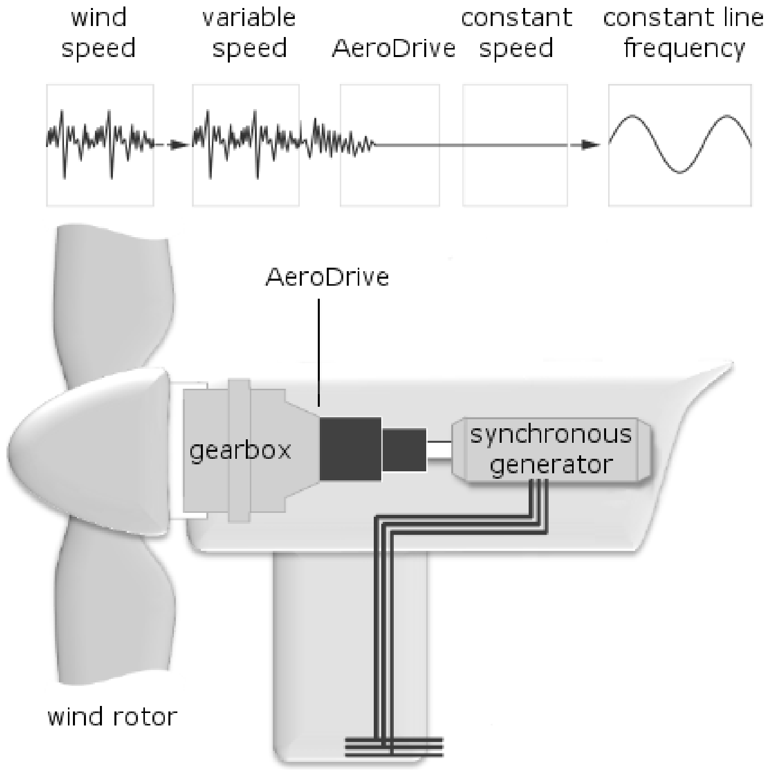


Figure 2.1.3: AeroDrive concept [6]

More detail information about WinDrive and its function can be found in Appendices B or in References [10], [6], [15].
The main advantages and benefits of WinDrive technology are:

- A standard synchronous generator directly connected to the grid produces electricity in a grid-friendly manner and with power plant quality.
- There is no frequency converter in the wind turbine as WinDrive replaces the power electronics that are failure prone.
- The WinDrive dampens dynamic loads that occur in the driveline and thus extends the lifetime of other driveline components.
- The WinDrive has a long lifetime - longer than the lifetime of the wind turbine itself.

2.1.2.3 Transducers

All parameters, in which vibration can be expressed (displacement, velocity, acceleration), can be measured by transducers, which can be classified in:

- absolute vibration measurement transducers;
- relative vibration measurement transducers.

It is necessary to determine which of those transducers are used for the vibration measurement and also specify their position. Nevertheless, most of the displacement transducers measure relative displacement, whereas the most common velocity and acceleration transducers measure absolute motion.[13]. All vibration sensors measure motion along their major axis. This fact should be taken into account when choosing the number of sensors to be used. Due to the structural asymmetry of machine cases, the vibration signals in the vertical, horizontal and axial directions (with respect to the shaft) may differ. In addition, measurements should be taken at exactly the same location to enable direct comparisons of data sets. Moving the probe only a small distance on a machine can produce drastically different vibration levels [14]. Therefore, it is tricky to compare vibration data from two different machines although they are of the same type.
Another very important aspect is the frequency range of transducers which must corresponds to usage and requested application.

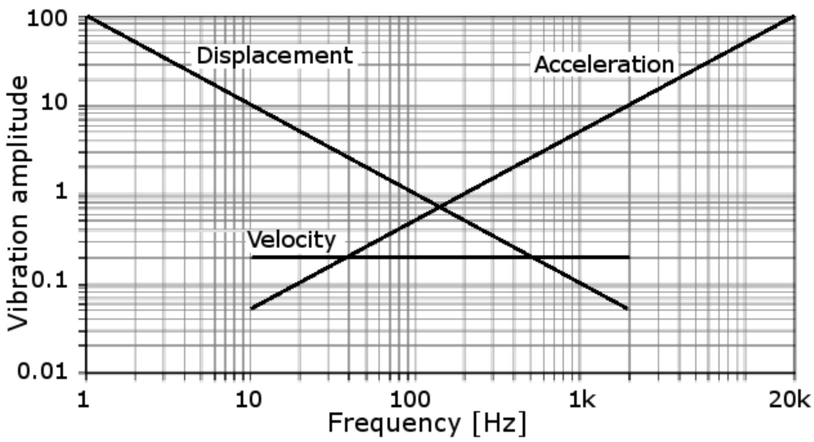


Figure 2.1.4: Vibration transducers - frequency range

Multibrid M5000 is equipped with 16 sensors providing vibration measurement. In Figure 2.1.5, the location of particular transducers is shown.

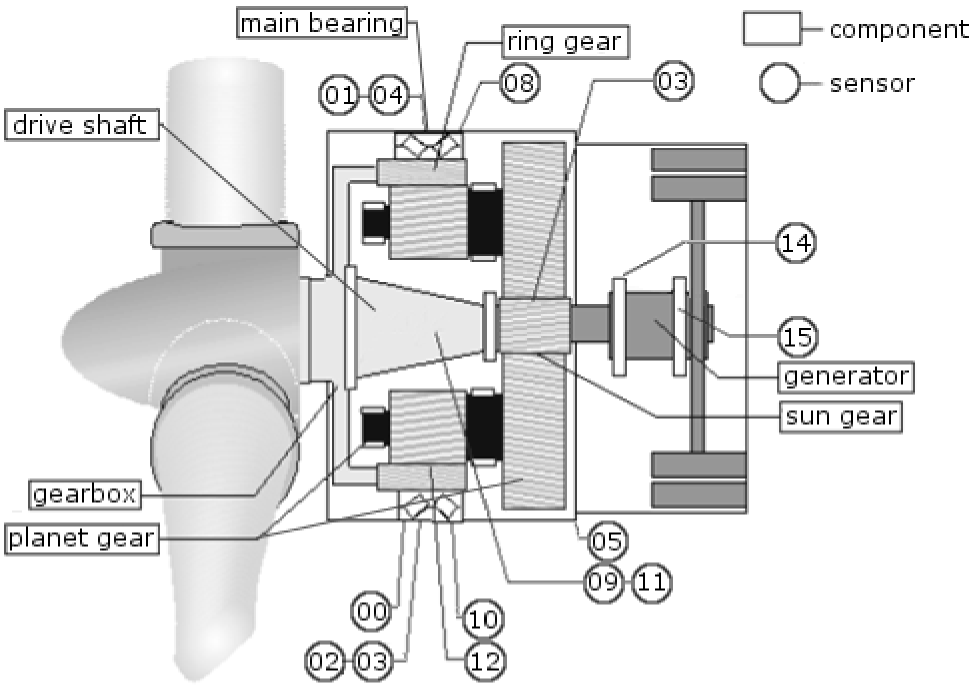


Figure 2.1.5: Location of sensors - Multribrid M5000

Speed is measured by a shaft encoder which generates a series of pulses at equal angular intervals. These series are converted into speed signal. Typical pulse count per revolution is 1024 (power of two), however, Multibrid M5000 is equipped with a 120-pulses-per-revolution encoder. The conversion to rotating speed is already carried out on the side of the data provider, therefore this work does not deal with it.

chan	variable	name	component	
00	force	HL_Bridge	gearbox	drive shaft planet gears
01	displacement	HL_weg_pos0		rotor bearing
02		HL_weg_pos90		
03		HL_weg_pos180		
04		HL_weg_pos270		
05	acceleration	Gondel	-	-
06	undefined	-	-	-
07	undefined	-	-	-
08	acceleration	HL_acc0	gearbox	drive shaft planet gear
09		HL_acc90		
10		HL_acc180		rotor bearing
11		HL_acc270		drive shaft bearing
12		PLST_1		planet gear ring gear meshing drive shaft bearing
13		PLST_2		planet gear drive shaft sun gear meshing drive shaft bearing
14		Gen_1	generator	drive shaft drive shaft bearing
15		Gen_2		drive shaft drive shaft bearing generator bearing

Table 2.1.1: Wind turbine Multibrid M5000 - sensors

2.2 Maintenance and health monitoring

To optimise running of machines, health monitoring systems and new maintenance strategies are developed to provide following benefits:

- increase in machine productivity;
- extend intervals between overhaul;
- minimize the number of overhaul;
- improve repair time;
- increase machine life;
- improve product quality;
- save maintenance cost.

The general health monitoring structure is already defined by International Standard Organisation (ISO) standards as well as maintenance principles. This section focuses on the branch of wind turbines and provides an overview of the way to ensure the benefits mentioned above.

2.2.1 Conditional-based maintenance

The goal of developing health monitoring systems is to enable Condition Based Maintenance (CBM), which constitutes a new maintenance paradigm. CBM has the potential to significantly reduce the cost of maintenance while the realiability and availability of the turbine is increased. Common maintenance strategies are:

- Reactive maintenance ("run-to-break");
- Preventive maintenance ("time-based");
- Predictive maintenance (CBM).

Reactive maintenance allows the equipment to run until it fails without maintenance intervention. This maintenance strategy ensures maximum operating time between shutdowns but also yields low reliability and high cost due to missed opportunities to detect and repair faults, secondary damage (progression of failure to severe sate), large logistics footprint to cope with unexpected failures, and lost production while equipment awaits repair.

Preventive maintenance can improve equipment reliability (number of failures) by periodically overhauling equipment before it wears out. To avoid unexpected failures in equipment that has an uncertain service life, preventive maintenance must be performed well in advance of the mean time to failure. Consequently, preventive maintenance achieves high reliability at the cost of performing premature maintenance. It leads to frequent interruption of production for planned maintenance, high labor costs, and high parts usage.

Conditional based maintenance enables high equipment reliability and low maintenance costs by eliminating the need for unnecessary overhaul activities while simultaneously allowing repairs to be performed on a planned basis. Detection of faults in their early stages provides an opportunity to order parts, schedule personnel, shutdown the equipment before serious damage occurs, and minimize downtime. However, this strategy requires having access to reliable condition monitoring techniques, which not only are able to determine current condition, but also give reasonable predictions of remaining useful life [13].

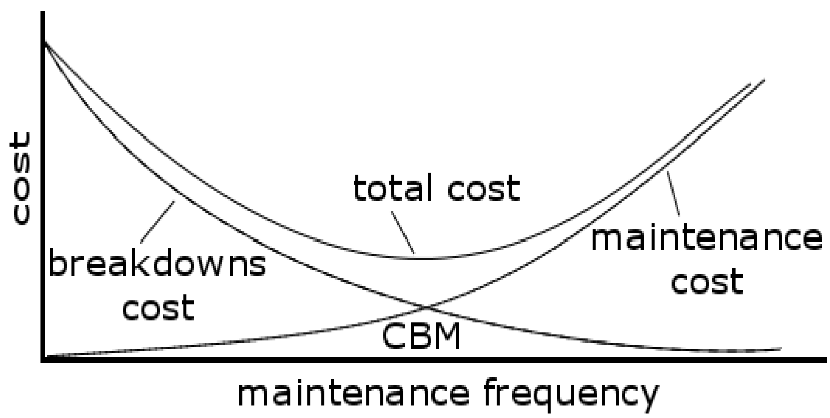


Figure 2.2.1: Cost of maintenance

2.2.2 Information flow structure

A combination of technologies should determine the cause and severity of possible faults and provide the justification for operations and maintenance actions.
In Figure 2.2.2, the recommended structure of data processing is shown. Particular task bay be carried out manually or automatically in order to implement condition monitoring successfully. The data flow starts with data acquisition block, where the monitoring configuration is specified for various sensors monitoring the equipment. Data transfer must be ensured among particular blocks and also external system (e.g. archive). The content of this section is based on ISO standards [1], [3] and [4].

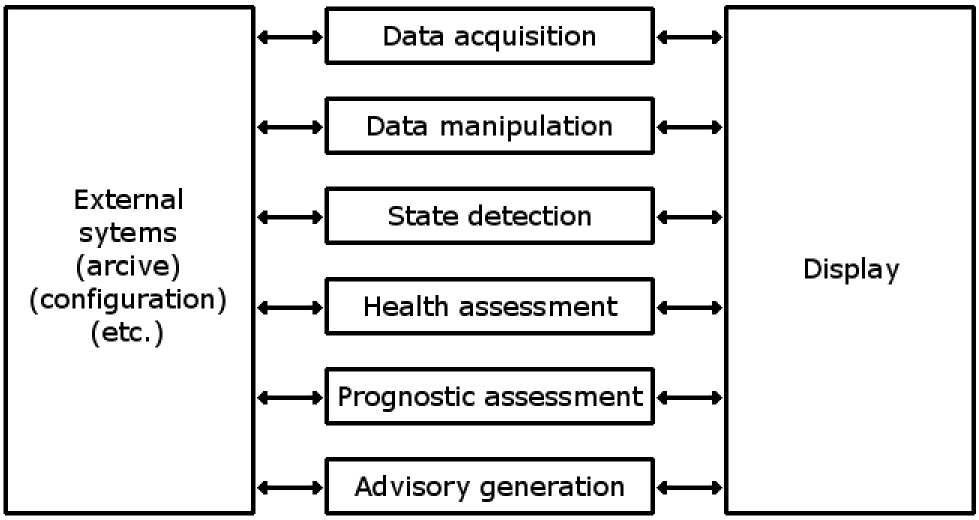


Figure 2.2.2: Data processing and information-flow diagram

Data acquisition block converts an output from the transducer to a digital parameter representing a physical quantity and related information such as the time (Coordinated Universal Time (UTC), local), calibration, data quality (e.g. "good", "bad", "unknown", etc.) and sensor configuration. It can be generalized to software module providing system access to digitized data and interface to a smart sensor.

Data manipulation block provides signal processing and analysis to compute meaningful descriptors (features) of interest in the machine condition monitoring and diagnostic process. It may contain processing functions such as Fast Fourier Transform (FFT), Order analysis, Wavelets etc.

State detection block compares outputs from preceding blocks against expected baseline profile values or operational limits, in order to generate enumerated state indicators ("alert", "alarm", etc.) with respect to boundary exceeding.

Health assessment block diagnoses any faults and rates the current health of the equipment or process, considering all state information from preceding blocks. This block contains specific assessment method(s) to generate current health grade and diagnose faults and failures with associated likelihood probability with respect to operational context. In addition, it may generate recommendations, evidence and explanation.

Prognostic assessment block determines future health states and failure modes based on the current health assessment and projected usage loads on the equipment and/or process, as well as remaining useful life predictions. To aid the assessment, the prognostic algorithm may use model based information, historical failure data and operational history.

Advisory generation block integrates information from all preceding and external blocks to provide optimized recommended actions and alternatives to applicable personnel or system. Recommendations may include prioritized operational and maintenance actions and capability forecast assessments or modifying operational profiles to allow mission completion.

2.2.3 Condition-based monitoring techniques

Condition monitoring includes many techniques, such as:

- Vibration monitoring
- Acoustic monitoring
- Oil analysis
- Particle analysis
- Corrosion analysis
- Thermography
- Performance monitoring.

This paper is focused only on vibration monitoring. Some aspects of this monitoring technique are mentioned in following paragraph.

2.2.3.1 Vibration monitoring

As mentioned above, health monitoring system includes many subsystems, but vibration monitoring is one of the most important. The major advantage is that vibration monitoring can detect the health condition of rotating components such as main bearing, gearbox and generator and identify developing problems before they becomes too serious.
Even in good condition, machines generate vibrations, which can be described with vibration levels such as Root Mean Square (RMS), mean, etc. Moreover, many such vibrations are directly linked to periodic events in operations of machine such as rotating shafts, meshing gear teeth, rotating electric fields, and so on. The frequencies with which such events repeat often gives a direct indication of the source and thus many powerful diagnostic techniques are based on frequency analysis [13].
All those types of vibration and their levels create together a specific vibration signature. While a fault is developing, the machine vibration signature is changing in a way that can be related to the fault. Vibration analysis helps to read this signature and its changes and detect the faults. That can be done

e.g. by trending vibration levels in time. Changes in trend may indicate developing fault. However, behaviour of vibration is not stationary because it is dependant on parameters such as operating load, rotational speed and dynamic stiffness. Therefore, the trend analysis (vibration analysis in general) must be carried out in respect to operating conditions. Fundamental methods for vibration analysis are described in Chapter 3.

2.3 Rotating machines faults

In this section, the most common faults on rotating machines are introduced. Usually, short description and the most significant symptoms are given. Information in more detail can be found in [12],[13] and [14].

2.3.1 Unbalance

Unbalance (imbalance) is defined by ISO as:

Condition which exists in a rotor when vibration force or motion is imparted to its bearings as a result of centrifugal forces [2].

In other words, unbalance happens when the local Centre of Mass (CoM) of the cross-section is not at the centre of rotation.

The unbalance force generating vibration is expressed as:

$$F = m \cdot r \cdot \omega^2, \tag{2.3.1}$$

where

m - mass,
r - radial displacement of the CoM from the centre of rotation,
ω - rotational speed of shaft.

Then

$$\text{unbalance vibration} = \frac{\text{unbalance force}}{\text{dynamics stiffness}}. \tag{2.3.2}$$

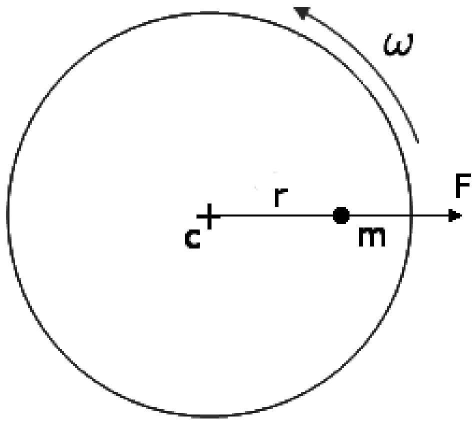


Figure 2.3.1: Unbalance description

Usually, all types of unbalance significantly excite 1X of radial vibrations and its amplitude varies proportional to the square of the shaft speed. However, the stiffness of the bearings support is usually nonlinear, therefore other higher harmonics may be also excited. Different types of unbalance can be distinguished by phase analysis of 1X.

2.3.2 Misalignment

When two or more shafts are coupled together, a misalignment may occur in vertical or horizontal direction. Basic types of misalignment may happen, namely:

- parallel misalignment;
- angular misalignment.

Pure parallel or angular misalignment is rare. Usually, a combinations of both mentioned types of misalignment are encountered.

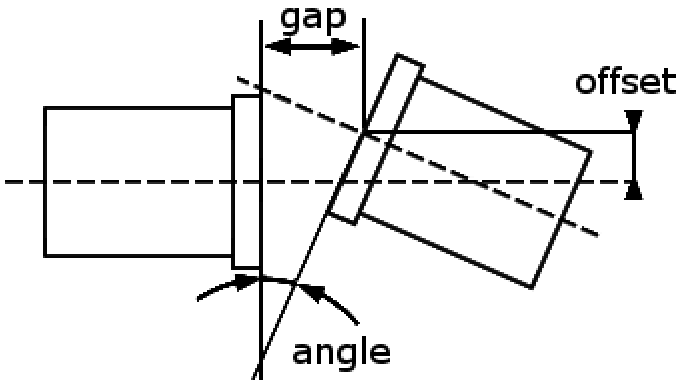


Figure 2.3.2: Misalignment

Angular misalignment primarily excites 1X of axial vibration whereas parallel one usually results in 2 hits per cycle and therefore 2X of radial vibration is excited. As mentioned above, conjunction of both types is often encountered. Then the dominant harmonics (1X or 2X) determine the type of misalignment.

When misalignment becomes severe, it can generate high amplitude peaks at much higher harmonics (3X to 8X) or even whole series of high-frequency harmonics.

2.3.3 Bent shaft

Bent shaft generates high vibration and creates a lot of stress on other components. A permanent shafts bow produces similar response as a combination of unbalance and misalignment (especially angular one). Axial vibration measurement on one of the bearings usually reveals excited 1X and 2X of the rotating speed. If the:

- amplitude of 1X is dominant then the bow is near the center of the shaft
- amplitude of 2X is dominant then the bow is closer to the coupling.

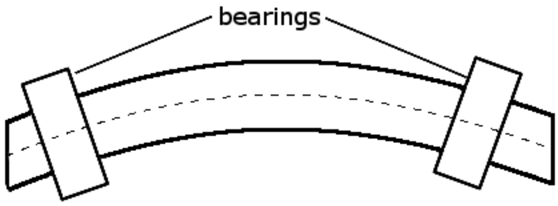


Figure 2.3.3: Bent shaft

The way to distinguish bent shaft from misalignment or unbalance is vibration phase measurement because the bent shaft is usually 180° out of phase in the axial direction.

2.3.4 Cracked shaft

A cracked shaft is one of the most serious fault, which can occur in a rotating machine, and it can be a cause of consequent failure and large damage of the whole equipment. The existence of a crack usually causes a significant change in the machine dynamic stiffness as well as in the normal vibration level. However, even a large crack has only a small effect on the natural frequencies of the shaft and almost none when the crack is closed. Therefore, the change of amplitude and phase of vibration harmonics is the symptom that must be monitored.
The type of crack depends on the shafts attributes and its classification is complicated. However, two most general groups of cracks can be specified:

- permanently open cracks;
- opening and closing cracks.

A crack can open and close during one revolution usually because of bow due to gravity. This behaviour affects primarily the first three harmonics of the shaft speed. Hence, it can be easily distinguished from unbalance or misalignment. In comparison, the permanently open crack affects especially the first and second harmonics, therefore, the phase analysis is necessary to

distinguish it from unbalance or misalignment.
Another suitable way to determine a crack is monitoring of features while speed is running up or down because the influence of a crack is more evident.

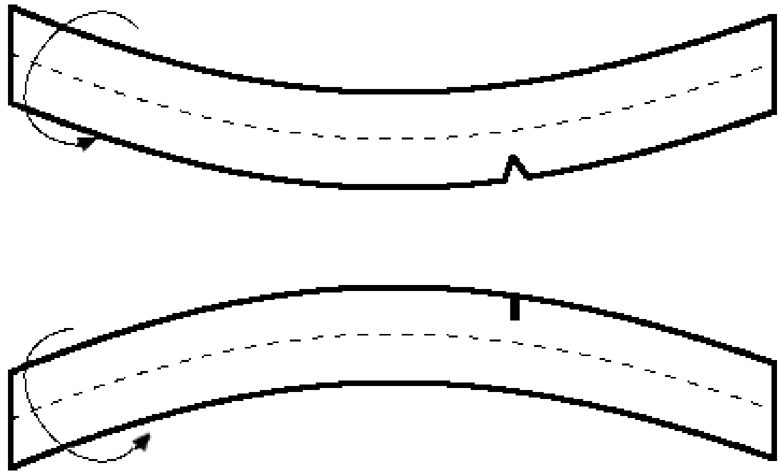


Figure 2.3.4: Closing and opening crack

2.3.5 Ecentricity

Eccentricity occurs when the center of rotation is at an offset from the geometric centerline of a sheave, gear, bearing, motor armature or any other rotor. The 1X of rotation speed of the eccentric component is excited to maximum amplitude in a direction through the centres of the two rotors, as shown in Figure 2.3.5. Here the amplitude varies with the load even at constant speeds.
In comparison to unbalance, when the transducer is moved from the vertical to the horizontal direction, a phase shift of 90° is observed. However in eccentricity, the phase readings differ by 0 or 180° when measured in the horizontal and vertical directions.

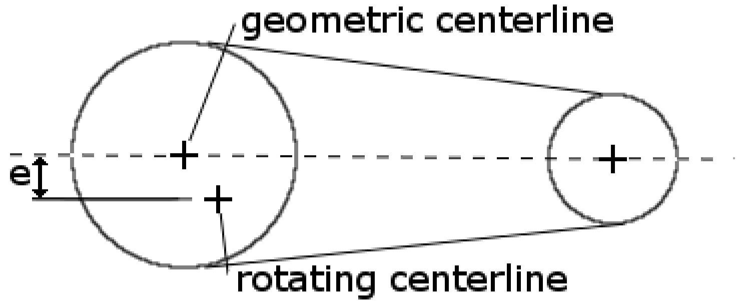


Figure 2.3.5: Eccentricity

2.3.6 Looseness

Looseness is normally caused by an improper fit between component parts. In rotating machines, different types of looseness can occur and produce many peaks in FFT spectrum due to its non-linearity. Many harmonics and also subharmonics (multiples of one half and one third of 1X, usually produced in bearings) are excited. Nevertheless, the phase behaviour is also non-linear, hence looseness can be distinguished from other mentioned faults such as unbalance or misalignment.

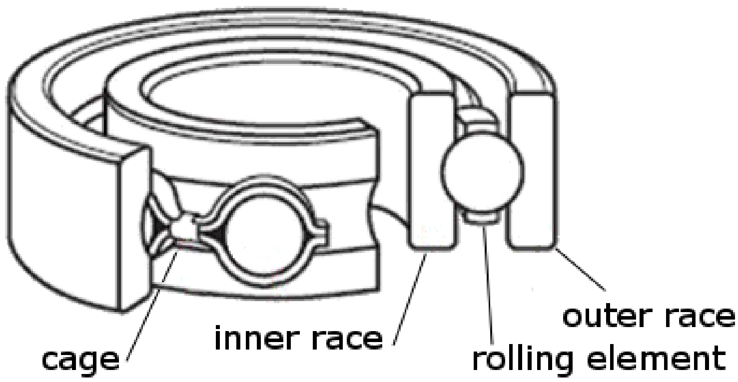


Figure 2.3.6: Bearing - looseness can occur between particular parts

2.3.7 Cocked bearing

A cocked bearing is a form of misalignment and appears when bearings are not accurately aligned with the shaft. Such cocked bearings usually produces considerable axial vibration, although the assembly is balanced. Harmonics 1X, 2X and 3X are excited. The cocked bearing can be distinguished from other types of faults by phase analysis because a twisting motion is caused with approximately 180° phase shift from the top-to-bottom [14].

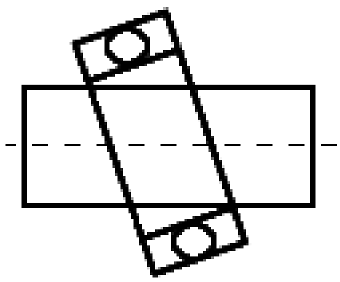


Figure 2.3.7: Cockded bearing

2.3.8 Rubbing

Rubbing phenomena occurs when the rotor rubs a stationary element. The impacts produce vibrations at the fundamental rotational frequency and its harmonics. The generated spectrum is similar to mechanical looseness, which is described in Section 2.3.6. Rubbing can be classified as:

- partial rubbing;
- rubbing throughout whole cycle (full annular rubbing).

Unfortunately, rubbing produces high frequencies similar to white band noise, therefore rubbing detection from FFT amplitude spectrum may be difficult. Therefore, the time-frequency domain methods are usually used. Another good indicator of rubbing is truncated waveform due to rub shown in Figure 2.3.8 and also orbit analysis.

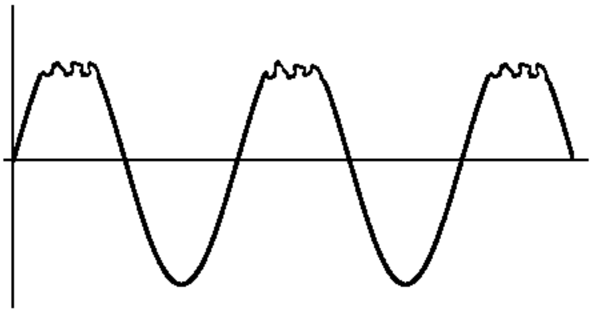


Figure 2.3.8: Truncated waveform due to rubbing

2.3.9 Bearing clearance

Bearing clearance exists between rolling elements (balls) and the inner and outer races of the bearing. It expresses the measure of the geometrical space between those parts.

High clearance in journal bearings in late stages can normally excite a whole series of running speed harmonics, which can be up to 10X or 20X. The FFT spectrum looks very much like that of looseness.

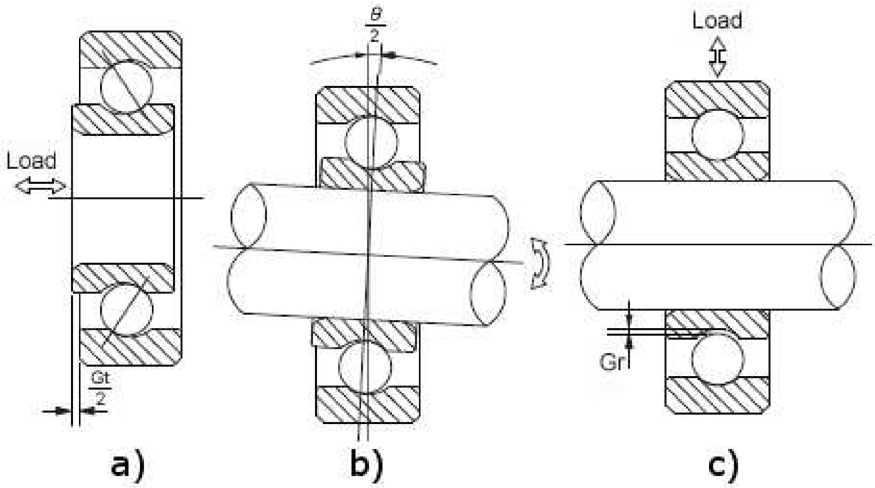


Figure 2.3.9: Clearance - a) axial, b) moment, c) radial

2.3.10 Gearing defects

In case of a gearbox, the spectrum can show the low harmonics as well as high harmonics. The reason is that the Gear Mesh Frequency (GMF) is a product of the number of teeth and rotating speed:

$$GMF = \text{number of teeth on pinion} \times \text{pinion speed in RPM} \qquad (2.3.3)$$

The spectrum usually show 1X and 2X of the speed, along with the GMF. Moreover, the GMF will have running speed sidebands relative to the shaft speed to which the gear is attached. These sidebands around GMF and its harmonics are quite common. Hence, the gearbox spectrum contains a range of frequencies due to different GMFs and their harmonics. If the gearbox is in a good condition, all peaks have low amplitudes and no natural frequencies are excited.

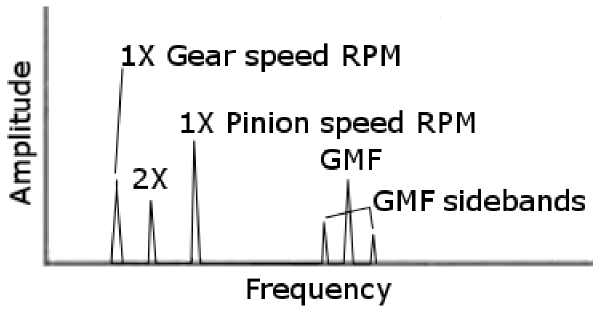


Figure 2.3.10: Normal gears spectrum

Gear tooth wear

When gear tooth wear occurs, natural frequencies are excited with sidebands, which are spaced with the running speed of the bad gear. The amplitude of sidebands around GMF is usually high, however the GMF amplitude may stay unchanged. Therefore, the sidebands are more suitable indicator of tooth wear than the GMF itself.

Gear tooth load

The GMF amplitude may increase in conjunction with the gearbox load, therefore, high GMF amplitudes do not necessarily indicate a trouble, especially if sideband frequencies remain low and no gear natural frequencies are excited. Hence, it is recommended to carry out vibration analysis on a gearbox when is transmitting maximum power. The results can be used as a baseline in examination during common running condition.

Gear eccentricity and backlash

Gear eccentricity, backslash or non-parallel shafts often cause high amplitude sidebands around the GMF. Furthermore, amplitude of gear vibration can modulate at the running speed of the other gear. This phenomenon can be observed in time domain waveform. Improper backlash usually excites the GMF and gear natural frequencies and their sidebands at 1X.

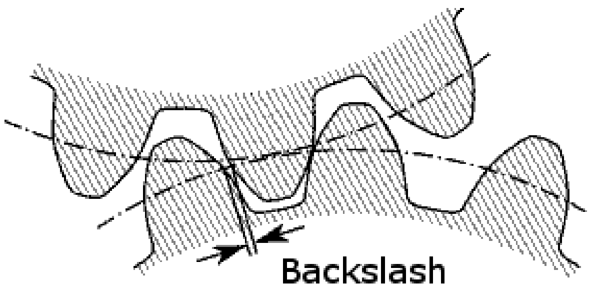


Figure 2.3.11: Gear backlash

Gear misalignment

Gear misalignment often excites 2X or higher GMF harmonics and their sidebands, which are spaced with the running speed. High amplitudes at 2X and 3X of GMF can be observed from FFT spectrum, whereas 1X of GMF stays low.

Cracked or broken tooth

A cracked or broken gear tooth can be fairly well detected from the time domain waveform because a spike is produced every time when damaged tooth tries to mesh with teeth on the mating gear. In FFT spectrum, a high amplitude at 1X of GMF can be observed and simultaneously gear natural frequency is excited together with its sidebands spaced with running speed.

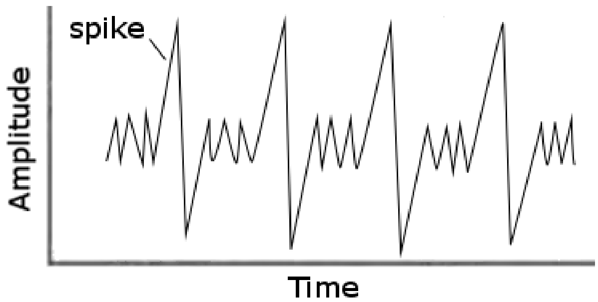


Figure 2.3.12: Broken tooth - time waveform

Hunting tooth

The gear hunging tooth can cause quite high vibration, but since it occurs at low frequencies, it is often missed during vibration analysis. The hunting tooth frequency can be expressed as:

$$\text{Hunging tooth frequency} = \frac{GMF \cdot N}{\text{no. of pinion teeth} \cdot \text{no. of gear teeth}}, \quad (2.3.4)$$

where

N - lowest common integer multiple between the number of teeth on the pinion and gear.
It it clear from the equation that the hunting tooth frequencies are very low.

Summary

Entire gearbox can generate a whole series of significant frequencies. At first, frequencies of interest must be defined. The calculation is based on the parameters of the gearbox, its gears and pinions. Then those frequencies should be identified in the spectrum analysis to verify the computation accuracy.

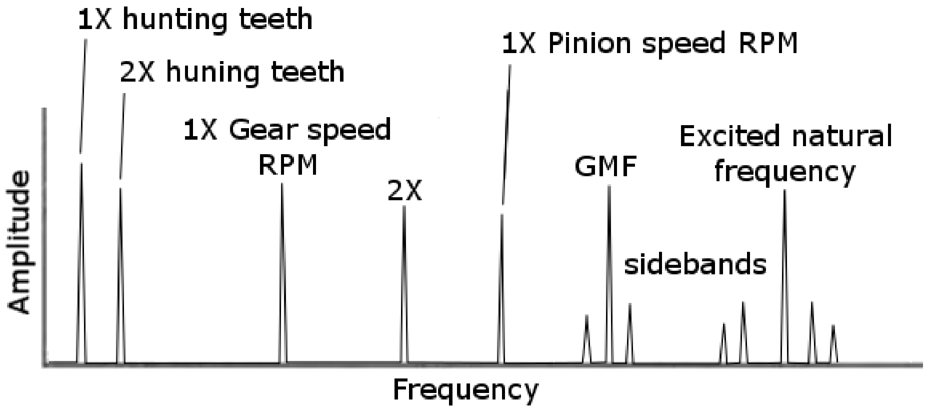


Figure 2.3.13: Gearbox spectrum example

3 Fault detection data processing

This section deals with methods used for data processing in this thesis. At first, feature extraction is described with the methods and features of interest. Then the feature reduction and its meaning are explained and also suitable method is suggested. Further the diagnostics methods for fault detection are provided. In case of the structure of HMS described in Figure 2.2.2, this section deals with blocks "Data manipulation" and "State detection".

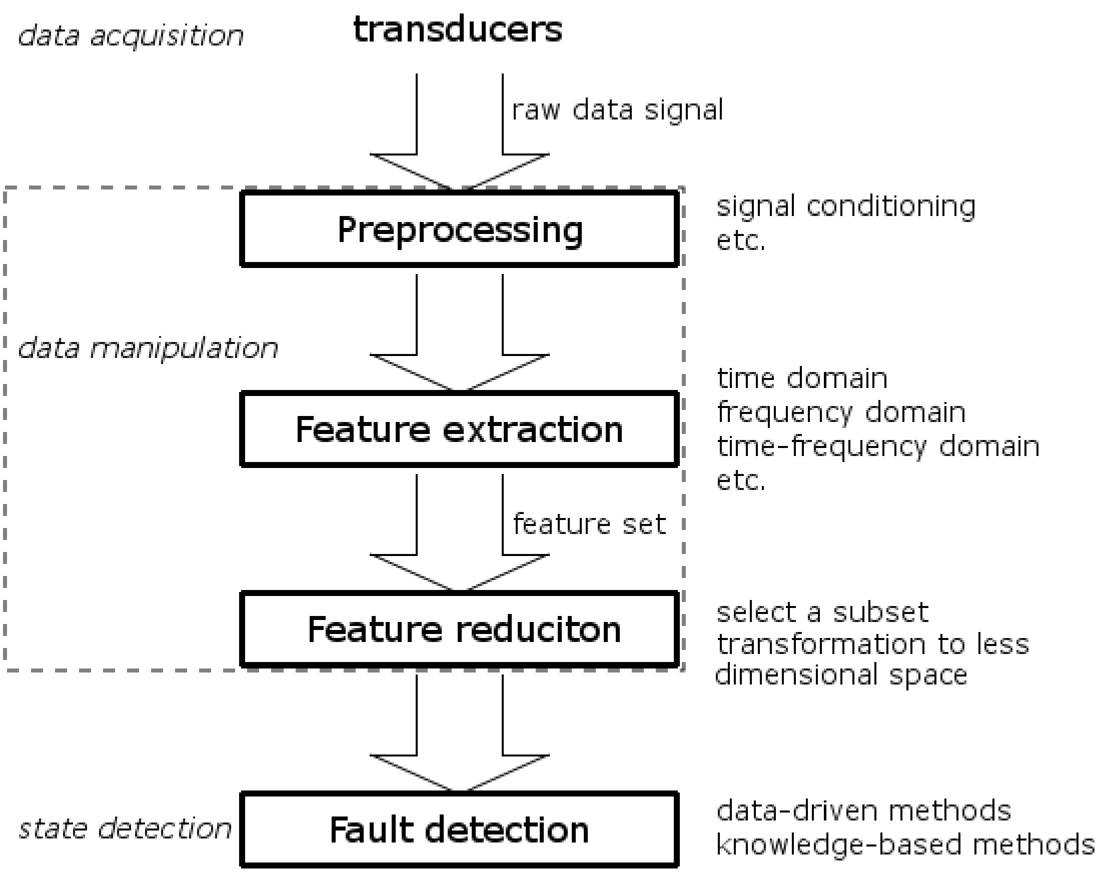


Figure 3.0.1: Data processing

3.1 Signal preprocessing

Usually, before any method for calculation of features of interest can be used the raw vibration data must be conditioned or preprocessed. The most common techniques are:

- Correction of vibrations range by multiplying the whole signal by some calibration constant which is based on used sensor.
- Offset correction.
- Removing the mean of the signal.
- Filtering (e.g. anti-aliasing filter due to FFT).
- Interpolation (e.g. merging signals with different sampling frequencies).
- Time synchronous averaging to extract repetitive signal from additive noise.
- Data integration or derivation.

All these techniques must be used reasonably in relation to the signal. In case of this thesis, the acquired data were not further preprocessed, however the final application contains the tools to perform some of the preprocessing techniques mentioned above.

3.2 Feature extraction

Usually, any types of defects or damage will influence the machinery behaviour which is measured by transducers and converted to electrical signals. These raw data signals are conditioned or preprocessed and after that, various methods are used to extract the features of interest, which are required to be ideally more stable and well behaved than the raw signal itself. The types of vibration analysis methods are shown in Figure 3.2.1. This work deals only with time-domain and frequency domain methods.

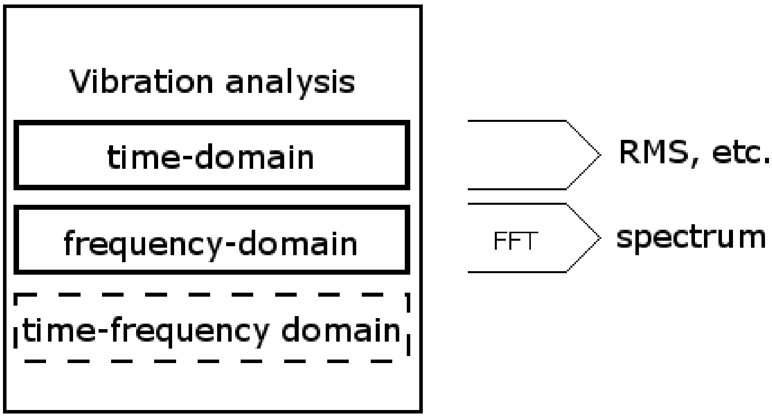


Figure 3.2.1: Vibration analysis

3.2.1 Time-domain analysis

The main benefit of time-domain analysis is that the features can be calculated rather simply and directly from the (preprocessed) raw signal. The meaning of these features is to characterize the whole time signal (statistical measures) and some of them may even indicate some faults, however, they cannot provide any information on which component the fault occurred. Nevertheless, trend of all these features can be examined over time and compared with baseline values to detect developing faults.
Some of the features can be more sensitive to load and speed of the equipment. Generally, when the feature has the same unit as the vibration signal such as mean, standard deviation, RMS, etc., then it is dependent on load and speed. On the other hand, when the feature is dimensionless such as crest factor, kurtosis, skewness, etc., then it is less sensitive to load and speed.
Some vibration levels and theirs limit values are described in ISO norms such as ISO 2372 where RMS alarms levels are defined.
Table 3.2.1 shows some of the time-domain statistical features, which can be calculated from vibration signal. The most common features for machinery industry are described in following sections in more detail.

Feature Name	Definition
mean	$\bar{x} = \frac{1}{N}\sum_{n=1}^{N} x_n$
average rectified	$x_{AVR} = \frac{1}{N}\sum_{n=1}^{N} \lvert x_n \rvert$
maximum (peak)	$x_{max} = max(x_n)$
minimum	$x_{min} = min(x_n)$
peak to peak	$x_{p2p} = maxx_n - minx_n$
RMS	$x_{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2}$
delta RMS	$x_{\triangle RMS} = x_{RMS}(t) - x_{RMS}(t-1)$
variance	$x_{\sigma^2} = \frac{1}{N}\sum_{n=1}^{N} (x_n - \bar{x})^2$
standard deviation	$x_{\sigma} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} (x_n - \bar{x})^2} = \sqrt{x_{\sigma^2}}$
crest factor	$x_{CF} \frac{x_{p2p}}{x_{RMS}}$
kurtosis	$x_{kurt} = \frac{\frac{1}{N}\sum_{n=1}^{N} (x_n - \bar{x})^4}{x_{\sigma}^4}$
skewness	$x_{skew} = \frac{\frac{1}{N}\sum_{n=1}^{N} (x_n - \bar{x})^3}{x_{\sigma}^3}$
clearance factor	$x_{CLF} = \frac{max(\lvert x_n \rvert)}{x_{AVR}^2}$
impulse factor	$x_{IF} = \frac{max(\lvert x_n \rvert)}{x_{AVR}}$
form factor	$x_F = \frac{x_{RMS}}{x_{AVR}}$

Table 3.2.1: Time-domain statistical features

3.2.1.1 RMS

The RMS of the vibration signal represents the measure of the power content in vibration. It is defined as:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2}, \tag{3.2.1}$$

where

x_n - n-th member of data series ,
N - number of points in data series.

Equation 3.2.1 shows that the RMS value is not sensitive to isolated peaks in the signal, thus these peaks do not increase its value. In general, the RMS value of vibration signal is used as a descriptor of the overall condition of the tested equipment. Its value usually increases when an equipment (e.g. gearbox) wears out or some kind of damage makes progress (e.g. pitting). RMS can also indicate a major out-of-balance in rotating systems. However, this parameter is dependant on load and speed and the monitoring system must take it into account.
The RMS is also used in other calculations such as crest factor or K-factor. In some cases, the RMS value can be used as stop condition when it exceeds a prior defined limit value.

3.2.1.2 Crest factor

The crest factor is a measure of existence sharp peaks in the vibration signal. It is defined as:

$$\text{crest factor} = \frac{\text{peak level}}{\mathrm{RMS}}, \tag{3.2.2}$$

where

peak level	- peak value (or peak to peak value) of the raw data,
RMS	- Root Mean Square of the raw data.

Equation 3.2.2 shows that peaks in the vibration signal will increase the crest factor value but RMS value may not show significant change. However, as the damage progresses the RMS value will increase whereas crest factor decrease. Therefore, crest factor is useful for indicating early stages of gear and bearing damage which just cause the peaks in the vibration. Typical faults which can increase the crest factor are tooth breakage on a gear or a defect on the outer race of a bearing or the rolling bearing faults In other words, crest factor indicates occurrence of impacts. A simple diagnostics method is often comparing crest factor of healthy bearing or gear to that of damaged one. Common value of crest factor during normal operations is in the range from two to six. A value above six is usually associated with a machinery problem.

3.2.1.3 Kurtosis

Kurtosis is the 4th statistical moment and expresses the relative spikiness (or flatness) of a time signal compared to its normal state. It is expressed as:

$$\text{Kurtosis} = \frac{\frac{1}{N}\sum_{n=1}^{N}(x_n - \bar{x})^4}{x_\sigma^4}, \tag{3.2.3}$$

where

$\bar{x}$	- mean value ,
x_σ	- standard deviation.

Normal state corresponds to the normal distribution which has its kurtosis value equal to three. Kurtosis value higher than three represents abnormality and is usually associated with the existence of major peaks. The greater the number of peaks in the signal, the larger is the kurtosis value. Kurtosis value should increase as a gear wears and breaks and it is also good indicator of incipient bearing defects.

3.2.1.4 Skewness

Skewness is the 3rd statistical moment and it represents the measure of symmetry (or asymmetry) of the probability density function around its mean. It is expressed as:

$$\text{Skewness} = \frac{\frac{1}{N}\sum_{n=1}^{N}(x_n - \bar{x})^3}{x_\sigma^3}, \tag{3.2.4}$$

where

$\bar{x}$ - mean value ,
x_σ - standard deviation.

A distribution (data set) is symmetric when the left and the right of the center point of Gaussian distribution looks identical. A symmetric distribution has a skewness value equal to zero. Negative skewness indicates that data are skewed left and positive one that data are skewed right.
Usually, a machine in good condition has a Gaussian distribution, whereas a damaged one has a non-Gaussian distribution (skewness is non-zero). Skewness is usually used as a proper indicator of incipient bearing defects together with kurtosis.

3.2.1.5 Others

In this section, meanings of other statistical parameters are explained. The equations can be found in Table 3.2.1.

Mean is the 1st statistical moment and indicates the center of the distribution.

Standard deviation is the square root of variance (2nd statistical moment) and expresses the measure of the preciseness of the data set, or more precisely, the dispersion of the data set.

Peak level is the maximum value of the signal in a selected time interval.

It is an indicator of occurrence of impacts and usually it is used in computation of others features such as crest factor, etc.

Clearance and impulsive factors are sensitive to the existence of sharp peaks as well as crest factor, therefore they are used as an indicator of faults involving impacting, such as rolling element bearing wear or gear tooth wear.

Form factor describes the waveform of the signal and it may be useful for bearings defects detection.

Delta RMS is the difference between two consequent RMS values. Meaning of this parameter is that it will increase more rapidly in case of damage occurrence than e.g. RMS. However, as well as RMS also delta RMS is dependant on load and speed.

3.2.2 Frequency-domain analysis

Time-domain analysis provides information that is not very sufficient and it is not possible to identify the particular components in the vibration signal. Fortunately, it is possible due to frequency-domain analysis which is based on the theory of Jean Baptiste Fourier:

> All waveforms, no matter how complex, can be expressed as the sum of sine waves of varying amplitudes, phase and frequencies.

This idea enables to transform the signal from time domain into frequency domain and vice versa. The output of frequency-domain analysis is frequency spectrum (amplitude, phase, power, etc.), which provides information about particular frequency components. The value of any interesting spectral component can be trend over time and the progress of the fault can be examined. However, the disadvantage of frequency-domain analysis is that a significant amount of information (transients, non-repetitive signal components) may be lost during the transformation process. This can be resolved by using time-frequency domain methods, which are not parts of this work.

In a majority of industrial applications, the discrete signal is acquired from the transducers, therefore Discrete Fourier Transform (DFT) must be performed.

3.2.2.1 Fast Fourier transform

FFT is the most common way to compute DFT, which is defined as:

$$X(k) = \sum_{n=0}^{N-1} x(nT_s) \cdot e^{(-j2\pi kn/N)}, \tag{3.2.5}$$

where

N	- total number of samples used for calculation DFT, length of DFT ,
k	- index of discrete frequency bins, k = 0,1,2,...,
n	- index of samples,
$x(nT_s)$	- samples at time $n \cdot T_s$, n = 0,1,2,...,
T_s	- sampling period.

FFT processes finite discrete time signal and returns finite discrete frequency spectrum. To ensure maximal computation rate, the length of the time signal must be power-of-two sized.

Frequency resolution and range

The frequency resolution (number of lines or bins) and frequency range depend on:

- sampling frequency,
- number of acquired points.

In other words, length of the time-domain signal determines the properties of the output of FFT.

The maximal frequency, which can be captured and displayed by FFT is dependant on sampling frequency. This relation is described by Nyquist-

Shannon sampling theorem:

$$f_{max} \leq \frac{f_s}{2} = f_{NQ}, \tag{3.2.6}$$

where

f_s	- sampling frequency,
f_{NQ}	- Nyquist frequency.

The frequency resolution is defined:

$$\triangle f = \frac{f_s}{N} = \frac{1}{t_s \cdot N}, \tag{3.2.7}$$

where

f_s	- sampling frequency,
t_s	- sampling period,
N	- total number of samples,
$N \cdot t_s$	- length of the waveform.

Aliasing

When the sampling theorem described by Equation 3.2.6 is not satisfied, which means that the time signal contains frequencies higher than Nyquist frequency, the phenomenon known as aliasing occurs. In the aliased signal, frequency components above Nyquist frequency appear as frequency components below Nyquist frequency. It leads to an erroneous representation of the signal.

To prevent aliasing, the anti-aliasing filter must be used before the signal is digitalized. The anti-aliasing filter is a low pass filter whose cut off frequency is equal to Nyquist one. After that, frequencies above Nyquist frequency are removed and aliasing effect cannot occur.

In practice, the cut off frequency of anti-aliasing filter is not equal to Nyquist one but a little bit lower:

$$f_{cutoff} = \frac{f_s}{2.56}. \tag{3.2.8}$$

The reason is that the anti-aliasing filter may roll off over time. Nowadays, the anti-aliasing filter became a common part of many measuring modules and it is usually adjusted automatically according to the specific sampling frequency.

Decibel

Amplitude or power spectra may be often displayed in logarithmic unit decibel (dB), which is unit of ratio between measured value and reference one. Logarithmic scale provides wider dynamics range and it is easy to see the small frequency components with the large ones simultaneously in one diagram.

Transformation to decibels from power values:

$$P_{dB} = 10log_{10}\frac{P}{P_{ref}}, \tag{3.2.9}$$

where

P	- measured power value,
P_{ref}	- reference power value.

Transformation to decibels from amplitude values:

$$A_{dB} = 20log_{10}\frac{A}{A_{ref}}, \tag{3.2.10}$$

where

A	- measured amplitude value,
A_{ref}	- reference amplitude value.

The reference value corresponds to 0dB and usually that value is chosen in terms of same convention such as $1V_{RMS}$ in case of amplitude or $1V_{RMS}^2$ in case of power. After that, the output units are dBV or dBV_{RMS}.

Windowing

Using windows correctly is critical parameter which can significantly affect the results of FFT.

In general, Fourier transform assumes that the time record is exactly repeated through all time and that signal contained in a time record are thus periodic at intervals that correspond to the length of the time record. However, this assumption is nearly impossible to ensure, therefore FFT displays spectral components or sidebands where none truly exist. This effect is known as spectral leakage.

The purpose of windowing is to ensure same value of the signal at the beginning and the end of the time interval. When the captured signal is weighted by window function, the marginal values of time interval are reduced to zero. Unfortunately, this affects the ability to resolve closed spaced frequencies because the spectral peaks are "smeared". Is is evident, that using window is certain compromise between quality and readability of the spectral components.

Even if FFT processes time interval without applying special window, actually the rectangular window with amplitude equal to one is used. For this reason, no window is often called the Uniform or Rectangular window. There are many kinds of window functions such as:

- Rectangular (Uniform)
- Flat top
- Hanning
- Blackman
- etc.

However, the most common window in vibration analysis are the first three ones mentioned above.

Usually, when the intent is to identify the presence of a signal component (a peak) at specific frequency, it is best to apply a rectangular window. But, if the amplitude of the peak is important, the flat top window is clearly the best [14].

Averaging

When one time record is processed by FFT, the result may include some peaks caused by a random vibration influence. To minimize this effect, a several time records are processed by FFT separately and the results are averaged to improve the results. However, this is possible only if the signal is stationary and linear. Several types of averaging exist and each of them has certain qualities,therefore the averaging type is chosen according to usage. The averaging types are:

linear - each FFT spectrum collected during a measurement is added to one another and then divided by the number of additions. This helps in obtaining repeatable data and tends to average out random noise. This is the most commonly used averaging technique.

exponential - the most recent taken spectra are considered to be more important than older ones, and thus given more mathematical weight when adding and averaging them. This is used for observing conditions that change very slowly with respect to sampling time.

peak hold - the peak value in each analysis cell is registered and then displayed. In other words, it develops an envelope of the highest spectral line amplitude measured for any average. This technique is used for viewing transients, such as coastdowns or random excitations that may be required during stress analysis studies [14].

Overlap averaging

When more than one average is used to calculate FFT spectrum, it is possible to use overlapping to improve calculation time. Instead of waiting for capturing entire new time record to perform next averaging, a part of already processed time interval can be append to the new one, which was captured during the computation of the previous spectrum. This method may be useful in on-line applications.

Types of spectra

The output of FFT is two-sided spectrum in complex form with real and imaginary parts. This spectrum must be scaled and converted to polar form to obtain magnitude and phase, which are most common form for spectra representation.

$$\text{Amplitude spectrum}_{2S}\,[V] = \frac{\sqrt{Re^2\{FFT(S)\} + Im^2\{FFT(S)\}}}{N} \tag{3.2.11}$$

$$\text{Phase spectrum}_{2S}\,[rad] = arctan\left(\frac{Im\{FFT(S)\}}{Re\{FFT(S)\}}\right) \tag{3.2.12}$$

The two-sided amplitude spectrum actually shows half the peak amplitude at the positive and negative frequencies. In practice, the negative part is meaningless, therefore the two-sided spectrum is converted to single-sided form by multiplying each frequency other than zero (DC value) by two and the negative part is discarded. After that, each peak of single-sided spectrum correspond to the peak amplitude of each sinusoidal components which are contained in the time-domain signal. Often, the amplitude spectrum is required in RMS value, therefore the single-sided non-DC components must be divided by the square root of two. It is based on the common relation between peak amplitude and RMS value:

$$\text{Amplitude spectrum}_{1S}\,[V_{RMS}] = \frac{\text{Amplitude spectrum}_{1S}^{(non-DC)}[V]}{\sqrt{2}}. \tag{3.2.13}$$

To obtain single-sided phase spectrum, the second half of the values must be discarded. Following formula describes the conversion of phase spectrum from radians to degree.

$$\text{Phase spectrum }[^\circ\,] = \frac{180}{\pi} \cdot arctan\left(\frac{Im\{FFT(S)\}}{Re\{FFT(S)\}}\right) \tag{3.2.14}$$

Often, the power spectrum is useful for measuring the frequency content. Single-sided power spectrum can be derived:

$$\text{Power spectrum }\left[V_{RMS}^2\right] = (\text{Amplitude spectrum RMS})^2 \tag{3.2.15}$$

3.2.2.2 Order analysis

The most common method to analyse vibration signal is FFT mentioned above. However, the necessary assumption of FFT is that the vibration signal must be stationary. It means, the signal is not changing over time. In case

of wind turbines (and most rotating machines in general), this assumption cannot be satisfied, because the rotating speed of the components is non-stationary due to changing wind speed. Non-stationary signal causes that the frequency bandwidth of each individual harmonic in FFT spectrum gets wider. As a result, some frequency components may overlap.
On the other hand, Order Analysis (OA) provides correct results even if the rotational speed changes over time. However, the output is not frequency spectrum but order spectrum. Order is defined as the normalization of the rotational speed, therefore:

- the first order corresponds to the harmonic at the same frequency as that of the rotational speed,
- the second order corresponds to the harmonic at twice the frequency of the rotational speed,
- the third order ...

When the rotational speed remains constant, the frequency spectrum and order spectrum can be convertible.

$$\text{Frequency} = \frac{\text{speed [RPM]}}{60} \cdot \text{Order} \tag{3.2.16}$$

$$\text{Order} = Frequency \cdot \frac{60}{\text{speed [RPM]}} \tag{3.2.17}$$

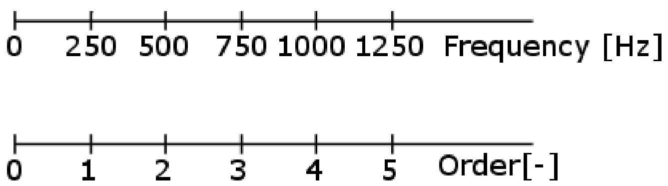


Figure 3.2.2: Frequency and order spectra: x-axis

The difference between OA and FFT is in data acquisition. The FFT use constant sampling frequency which defines the number of samples captures during one second. In case of OA, that is replaced by the number of points captured (sampled with constant sampling frequency) during one whole revolution of e.g. shaft. Since the rotation speed is not stationary, thus the number of samples captured during one revolution is not constant. To get the fix number of points for every revolution, the interpolation and resampling operations are applied on the captured data. After that, the standard FFT can be performed. Therefore, the OA provides the same quality as the FFT and simultaneously it can be used for non-stationary signal.

3.3 Feature reduction

In layman's terms, it seems the more features is extracted during the measurement the more accurate fault detection will be. However, this idea is not correct because most machine learning techniques, including fault detection methods, may not be effective for high dimensional data. The reasons are:

- curse of dimensionality and overfitting;
- query accuracy and efficiency;
- visualisation (projection of high-dimensional data onto 2D or 3D);
- data compression.

Feature reduction is possible due to information redundancy in the data because many of the features may be correlated with each other. Moreover, many of the features will have a variation smaller than the measurement noise and thus will be irrelevant [7]. Hence, a new set of the most representative features should be found. The feature (dimension) reduction techniques can be broken into:

- Selection-based techniques
- Transformation-based techniques

Feature selection is a process of selecting a subset of the original data with sufficient amount of information. The main advantage is that the physical meaning of the original features is retained. However, that is not true in case

of transformation-based methods which converts the original date to different space. The new space is usually less dimensional than the origin.
Many methods of both mentioned types exist and new methods are being developed because the dimension reduction is still an open problem. In following sections, one selection-based method and one transformation-based method are discussed.

3.3.1 Preprocessing

The extracted data of features must be preprocessed as well as row vibration signal before own processing. In case of this work, the indication of "bad" measurement was not included in the input data. The "bad" measurement means that the vibration signal was not acquired in proper conditions, thus the computed vibration levels such as RMS, crest factor, may reach unreasonable values. Those events are usually accidental and therefore random peaks can be observed, when the trend of some feature is plotted over time.

3.3.1.1 Median filter

Median filter is a non-linear digital filtering technique, which is usually used to remove noise. It can be successfully used also for elimination of random peaks mentioned above, but the side effect is that it also blurs surrounding values. Median filter is defined as:

$$y_i = \mathrm{median}(J_i) \tag{3.3.1}$$

where

J_i	- subset of the input sequence centred about the i-th element,
i	- index of sample, $i = 0, 1, \cdots, n-1$.

The subset J_i may not be centred equally as shown in Figure 3.3.1.

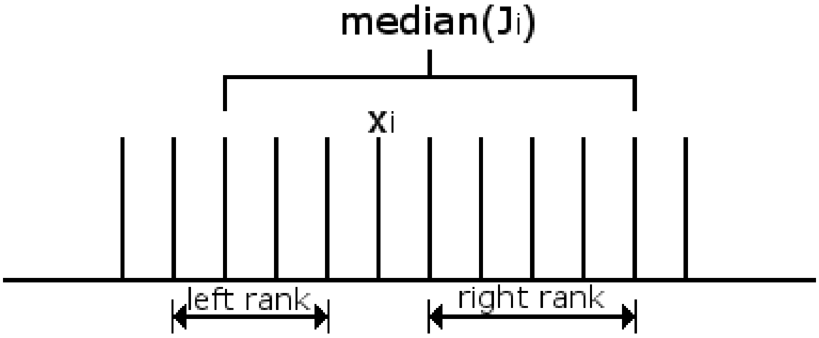


Figure 3.3.1: Median filter

3.3.2 Feature transformation

As mentioned above, transformation-based methods transform the origin data set to a new space, which is less dimensional. The transformation-based methods can be divided into linear and non-linear types and some of them are listed below:

- Linear
  - Principal Component Analysis (PCA)
  - Independent Component Analysis
  - Latent Dirichlet Allocation
  - ...
- Non-liner
  - Non-linear Principal Component Analysis
  - Principal curves
  - Neural networks
  - ...

In Section 3.3.2.1, PCA is described in more detail.

3.3.2.1 Principal component analysis

PCA is possibly the dimension reduction technique most widely used in practice and it is often used as a part of other more complex techniques. PCA is a simple transformation method based on eigenvectors which transforms d possibly correlated features into p uncorrelated features called principal components, where $p \leq d$. The first principal component corresponds to the largest eigenvalue of the covariance matrix, and therefore has the largest variation. It means that it contains most information which can be used in the following processing.
At the beginning, there are d column vectors $m \times 1$. Each vector v_i corresponds to a feature and each item of the vector corresponds to a measurement. These measurement vectors create a $m \times d$ matrix M.
At first, all vector must be normalized to ensure unit variance, therefore the mean value $\bar{v}_i$ of the vector is subtracted and the rest is divided by standard deviation σ_i of the original vector.

$$v_i^n = \frac{(v_i - \bar{v}_i)}{\sigma_i}, \text{ (element-by-element)} \tag{3.3.2}$$

The normalised vectors create a $m \times d$ matrix M^n.

$$M^n = [v_1^n, v_2^n, \cdots, v_d^n]$$

Then, the covariance $d \times d$ matrix C of the matrix M^n is determined and its eigenvalues λ_i and eigenvectors e_i are calculated.
After that, the eigenvalues λ_i are sorted decreasingly.

$$\lambda_1 > \lambda_2 > \cdots > \lambda_d$$

Subsequently, the eigenvectors e_i are sorted according to the sorted eigenvalues and create a new $d \times d$ matrix T.

$$T = [e_1, e_2, \cdots, e_d]$$

Finally, the transformation can be performed.

$$Y = M \cdot T \tag{3.3.3}$$

As mentioned above, the amount of information corresponds to the size of eigenvalues. The sorting of eigenvalues and eigenvectors ensure the most informative features correspond to the main principal components. The feature reduction can be done by leaving out the smallest eigenvalues and corresponding eigenvectors. After that, the transformation $d \times p$ matrix T is obtained and subsequently the output $m \times p$ matrix Y, where $p \leq d$.

3.3.3 Feature selection

As mentioned above, the benefit of selection-based method is that the physical meaning of dimension is preserved. The main assumption is that some features may contain the same information and therefore the redundant features can be removed. Selection-based methods for feature reduction can be broken into:

- filters
- wrappers
- embedded.

The methods are usually iterative to find the optimal subset of features. Filters use a criteria function to evaluate the selected subset and thus filter(remove) redundant features. Wrappers are similar to filters but the selected subsets are evaluated by the performance of a model. On the other hand, embedded methods apply a specific model straightly associated with the target learning machine.

3.3.3.1 Correlation-based method

In this thesis, the correlation-based filter method is used to reduce the high-dimensional space whereas the meaning of the features is preserved. The method is based on mutual correlation of a feature pair x^k and x^l, which is defined as:

$$r_{x^k,x^l} = \frac{\sum_{i=1}^{n}(x_i^k - \bar{x}^k)(x_j^l - \bar{x}^l)}{\sqrt{\sum_{i=1}^{n}(x_i^k + \bar{x}^k)^2 \sum_{i=1}^{n}(x_i^l + \bar{x}^l)^2}}, \tag{3.3.4}$$

where

$\bar{x}^k$ - sample mean of x^k,
$\bar{x}^l$ - sample mean of x^l,
n - number of samples in the feature vectors x^k and x^l.

When two features are independent, the mutual correlation $r_{x^k,x^l} = 0$. The mutual correlation can be calculated for all features in the data set X and average absolute mutual correlation of a feature over δ features can be defined as:

$$r_{j,\delta} = \frac{1}{\delta} \sum_{i=1, i\neq j}^{\delta} |r_{x^k,x^l}|. \tag{3.3.5}$$

The features α which has the largest average mutual correlation

$$\alpha = \operatorname*{argmax}_{j} r_{j,\delta} \tag{3.3.6}$$

is removed from the data set X. Then the whole process can be applied again to remove another feature but to the new reduced subset.
This technique removes the most correlated (redundant) features one by one till the required number of features d remains. The problem is to determine the size of d to ensure certain amount of information in final subset. To resolve this issue, the idea about eigenvalues of covariance matrix described in the PCA section was adopted.
The sum of eigenvalues of covariance matrix of the original dataset X represents the total amount of information. Each subset of X has this sum

lower, therefore the required amount of information can be specified at the beginning at a percentage of the amount of total information. When the feature to remove from the set is determined, the sum of eigenvalues can be determined and if the amount of information is over the specified level, the feature is really removed. The whole feature reduction algorithm is described in Figure 3.3.2.

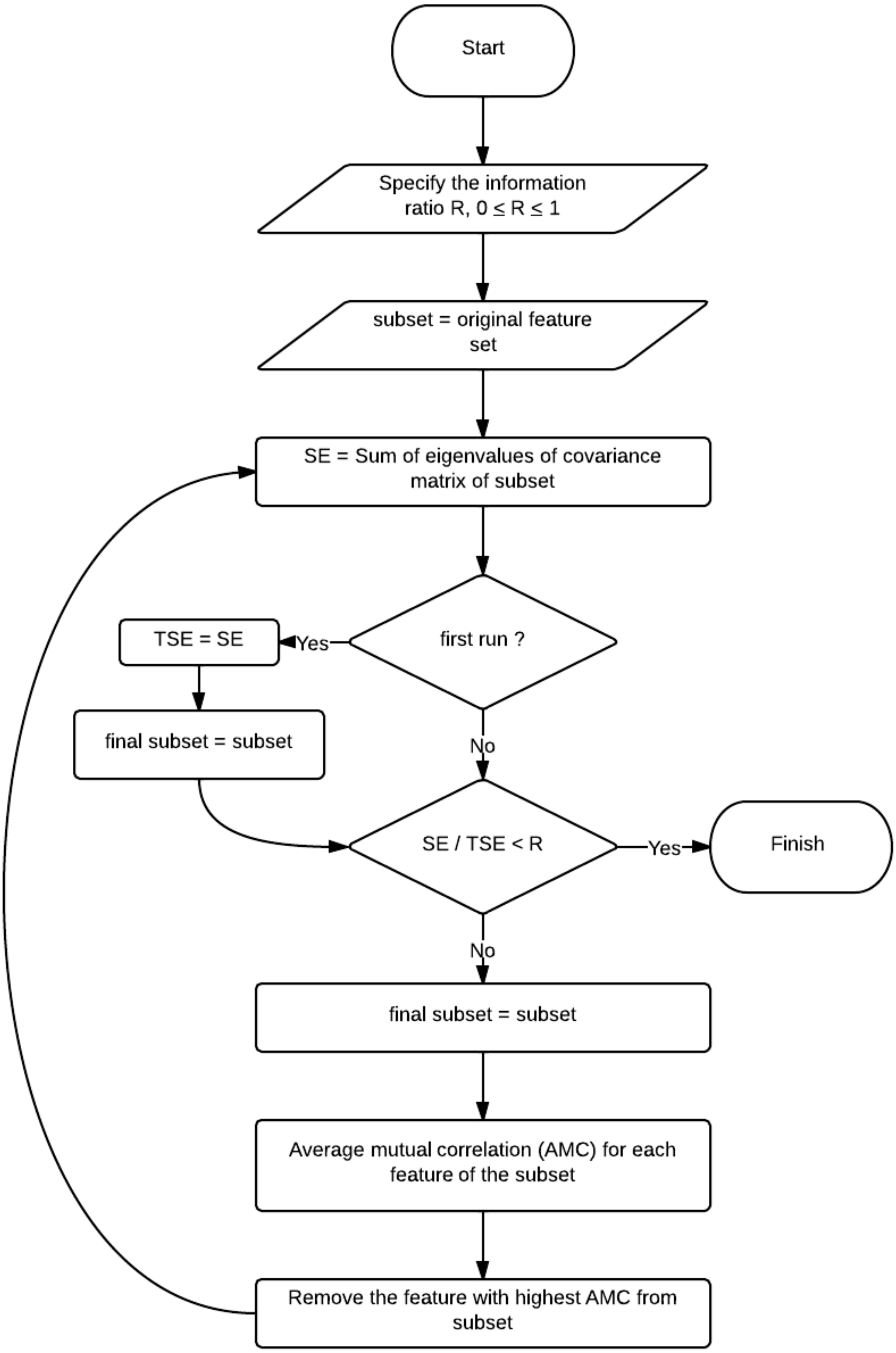


Figure 3.3.2: Feature selection algorithm

3.4 Fault detection

The fault detection is usually carried out by making a comparison between present descriptors of a machine and reference (baseline) values. Two main approaches defined in ISO standard ISO13379-1 can be used for diagnosing the condition of the machine.

Data-driven approaches (simple trending, neural network, pattern recognition, statistical, histographic Pareto approach or other numerical approaches). These methods are generally automated, do not require deep knowledge of the mechanism of fault initiation and propagation, but do require training the algorithm using a large set of observed fault data.

Knowledge-base approaches, which rely on an explicit representation fault behaviour or symptoms through, for example, fault models, correct behaviour models or case description [4].

This paper falls within the data-driven approaches such as:

- statistical data analysis and case-based reasoning
- neural networks
- classification trees
- random forests
- logistic regression
- support vector machines.

All methods mentioned above are fully described in ISO13379-1 as well as pros and cons. In case of this thesis, the statistical data analysis approach was chosen because of its simplicity and transparency. Also, the conclusion from [11] was considered.

3.4.1 Pattern classification

Pattern classification belongs to the statistical data analysis methods for the fault detection as mentioned above. This section is based on [11], where the pattern classification is described and evaluated as a proper method for fault (event) classification in comparison to others.
In case of this thesis, the goal is to realize unsupervised pattern classification, which means that the input patterns (data) are not associated with any specific situation (fault).The classification procedure can be divided into two steps:

- clustering
- classification.

3.4.1.1 K-mean clustering

Clustering or cluster analysis is primarily used to understand (explore) data when there are:

- unknown number of classes
- no prior knowledge.

When the classes are not defined a priori, the cluster analysis must be performed on training data set (patterns) to identify particular clusters which are then described in suitable form. The clustering methods divide the data set into relative homogeneous subsets (clusters) within the patterns are as similar as possible.
Many types of clustering methods exist which divide data into clusters according various criteria. In practice, the most common clustering method is K-mean algorithm which divide data set containing n samples into k clusters according to the mean distance. The number of clusters k must be specified at the beginning. The algorithm is numerical, unsupervised, nondeterministic and iterative clustering method which always divide data into k clusters without overlaps. Each point belongs to the cluster with near-

est mean (distance) to its centre. In another word, the algorithm tries to find k centres in the d dimensional space to minimize the sum of squares of Euclidean distance among n samples and k centres. It can be defined as

$$\underset{S}{\operatorname{argmin}} \sum_{i=1}^{k} \sum_{x_j \in S_i} \parallel x_j - \mu_i \parallel^2, \tag{3.4.1}$$

where

k	- number of clusters,
x	- data sample,
μ	- centre of cluster,
S_i	- data subset, $S = \{S_1, S_2, \cdots S_k\}$.

K-mean algorithm described in detail can be found e.g. in [8], [16].

3.4.1.2 Bayesian classification

Pattern recognition is the scientific discipline whose goal is the classification of objects into a number of categories or classes [16]. When the classes are not a priori known, the unsupervised pattern recognition is applied to the training data set to identify the classes. This thesis deals with statistical classifier which use a mathematical function to express the measure that the classified sample (pattern) belongs to the respective class. After that, usually the class corresponding to the maximal value of the measure is chosen.

The most common statistic classification method is based on Bayes's theorem which is well known and described e.g. in [8], [16]. The Bayesian classifier is the most widespread approach based on stochastic characterisation of patterns, assuming that the patterns are generated by a probabilistic system. It use the probabilistic Gaussian discriminant function for the classification and suppose, that the distribution of pattern in particular classes has the same shape of defined distribution [11].

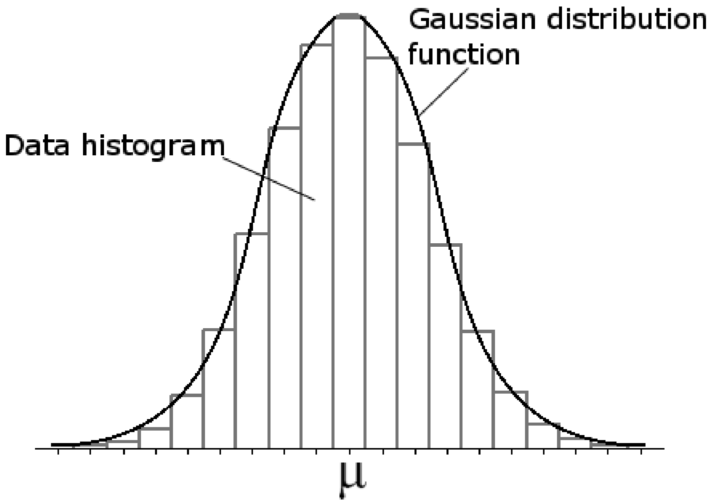


Figure 3.4.1: Gaussian distribution function

In the terms of own classification, the most important part is the formula defining the multivariate Gaussian distribution correlated in dimension as:

$$y = \frac{1}{(2\pi)^{n/2}\sqrt{\det C}} \cdot e^{-\frac{1}{2}(x-\mu)^T C^{-1}(x-\mu)}, \tag{3.4.2}$$

where

n	- number of dimensions,
C	- covariance matrix of the class,
μ	- sample mean of the class,
x	- data sample.

During the classification procedure of the sample x, the Gaussian distribution value y_i is determined for each class γ_i defined with its covariance matrix C_i and its mean μ_i. Then, the class γ with maximal value y_i is chosen as the most probably one to which the sample belongs.

$$\gamma = \operatorname*{argmax}_i y(\gamma_i) \tag{3.4.3}$$

4 Experimental data

In this section, the real data from a wind power plant are described and examined. Namely, the vibration data were acquired during the years 2011 and 2012 from the sensor no. 8 (See Table 2.1.1).

4.1 Raw data

The raw vibration data are acquired from sensors described in Table 2.1.1. Measurements are carried out at irregular intervals. Usually, at least one measurement per day is performed, when the power plant is not cut off. During the measurement, about 200 seconds of vibration signal is usually acquired simultaneously with the rotating speed signal of the main shaft. Figures 4.1.1 and 4.1.2 show correctly acquired data.

Unfortunately, the measurement is carried out independently on working conditions of the wind power plant. Thus, the data can be acquired even if the wind turbine is not working properly such as when the blades are not rotating or when the gondola is changing position. Then the acquired signal contains disturbing components, which are ineligible. Figures 4.1.4, 4.1.6, 4.1.8 show clear difference from acquired data in Figure 4.1.2. Changing working condition can be also clearly distinguished from speed data in Figures 4.1.1, 4.1.3, 4.1.5, 4.1.7.

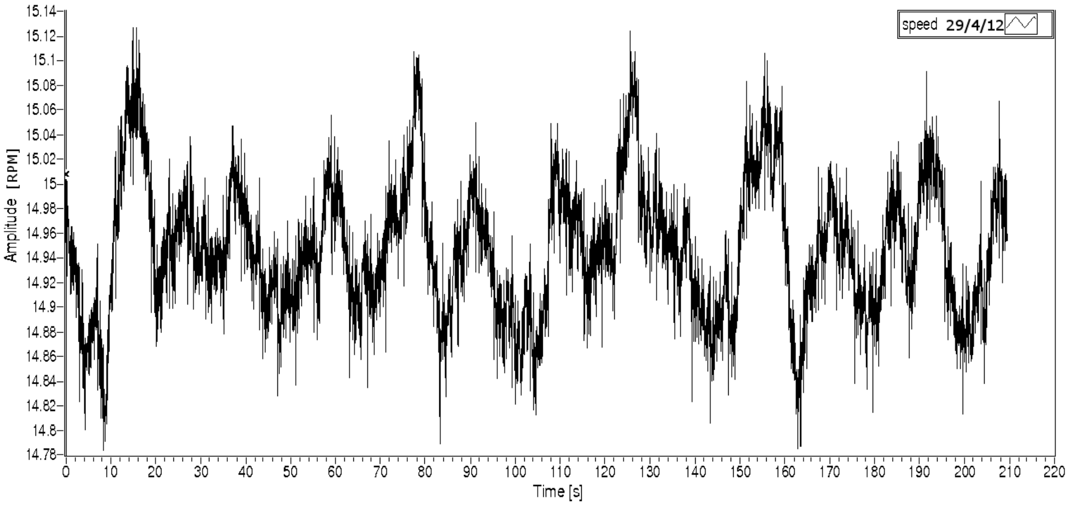


Figure 4.1.1: Speed data acquired 29/4/12

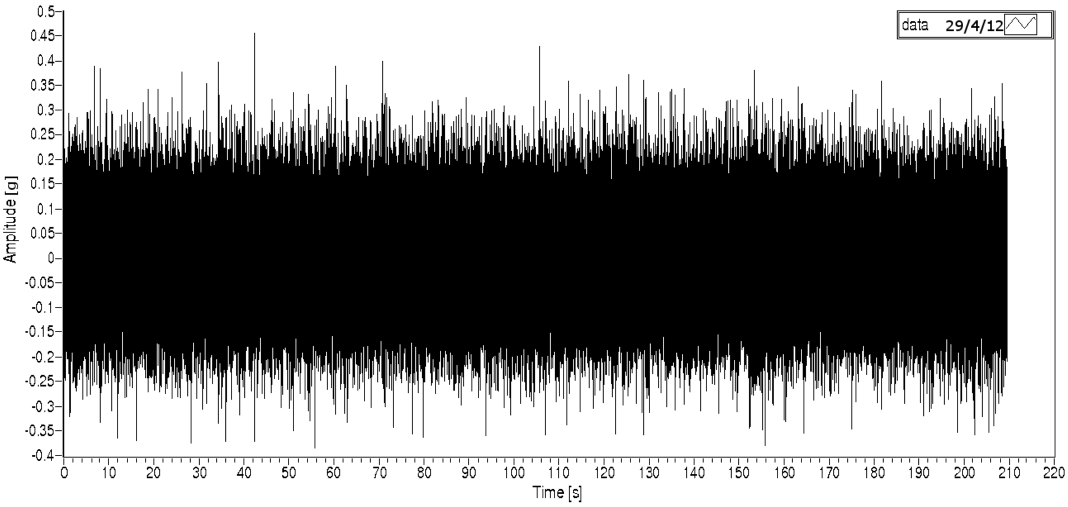


Figure 4.1.2: Vibration data acquired 29/4/12

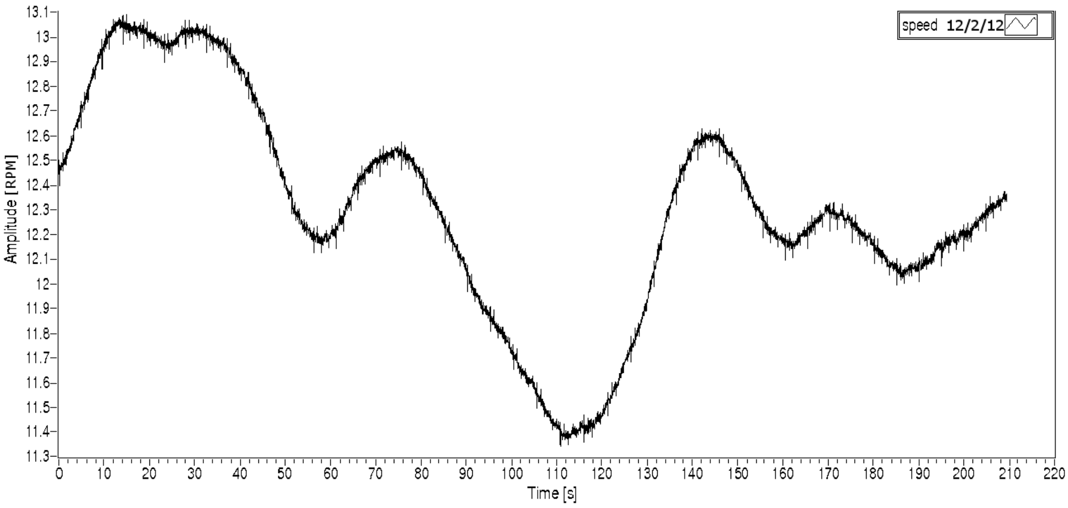


Figure 4.1.3: Speed data acquired 12/2/2012

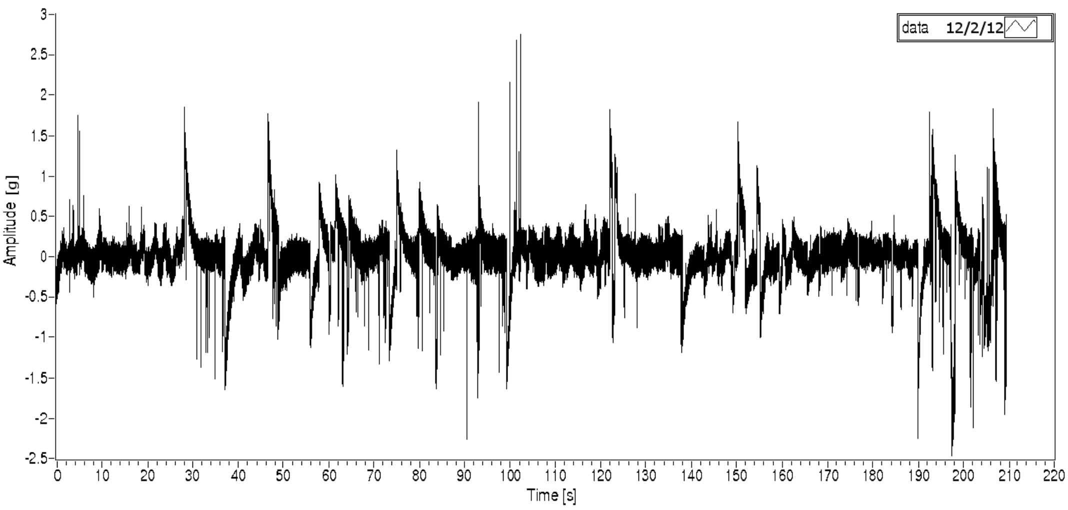


Figure 4.1.4: Vibration data acquired 12/2/2012

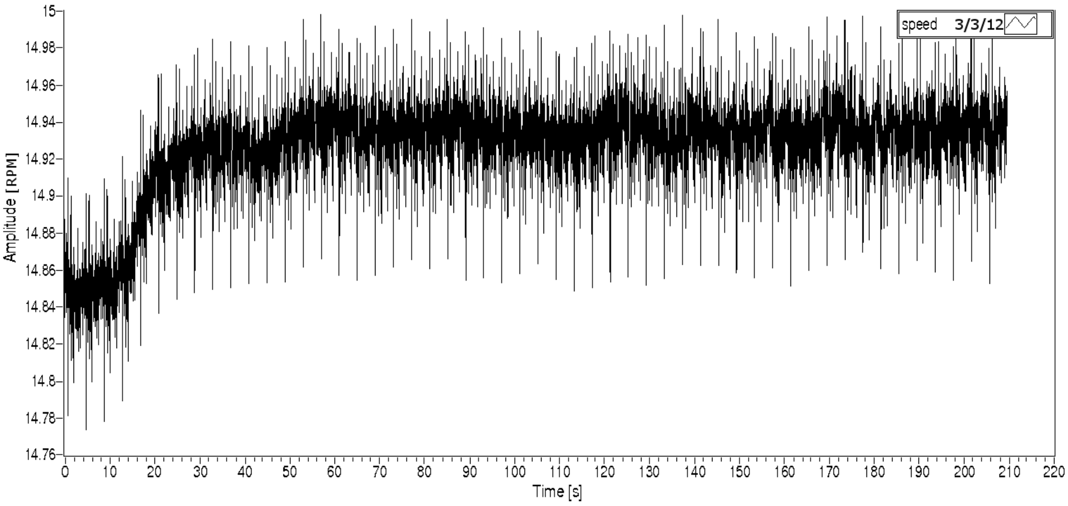


Figure 4.1.5: Speed data acquired 3/3/2012

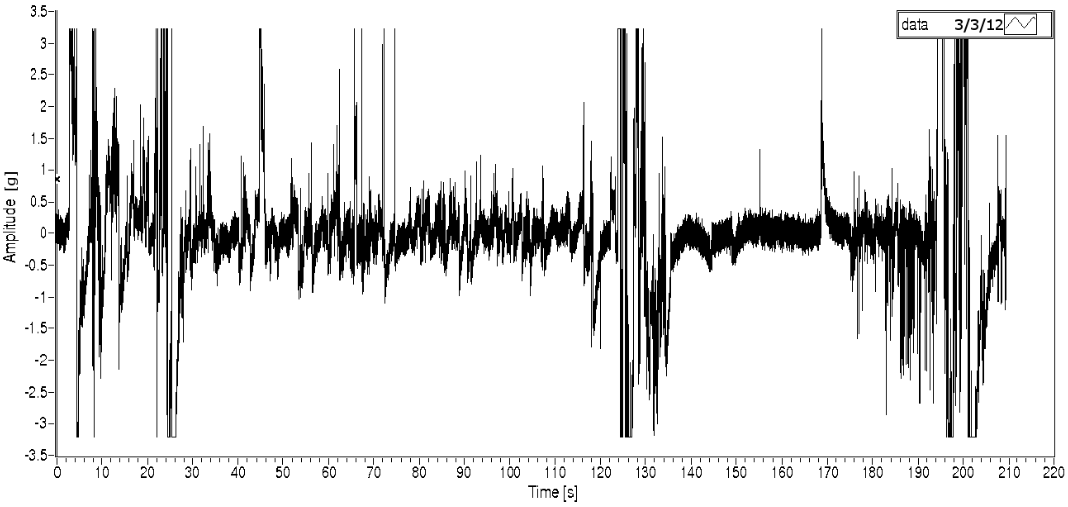


Figure 4.1.6: Vibration data acquired 3/3/2012

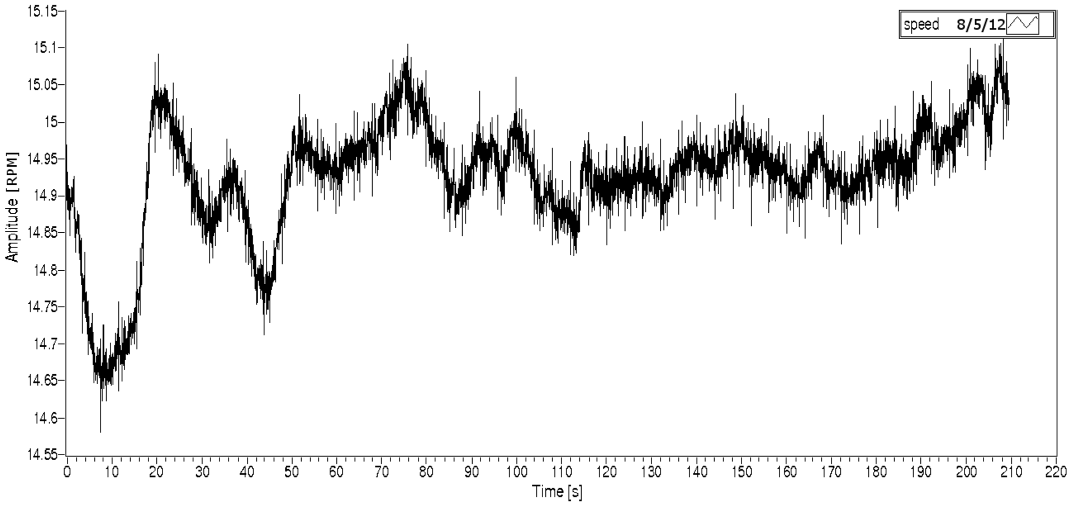


Figure 4.1.7: Speed data acquired 8/5/2012

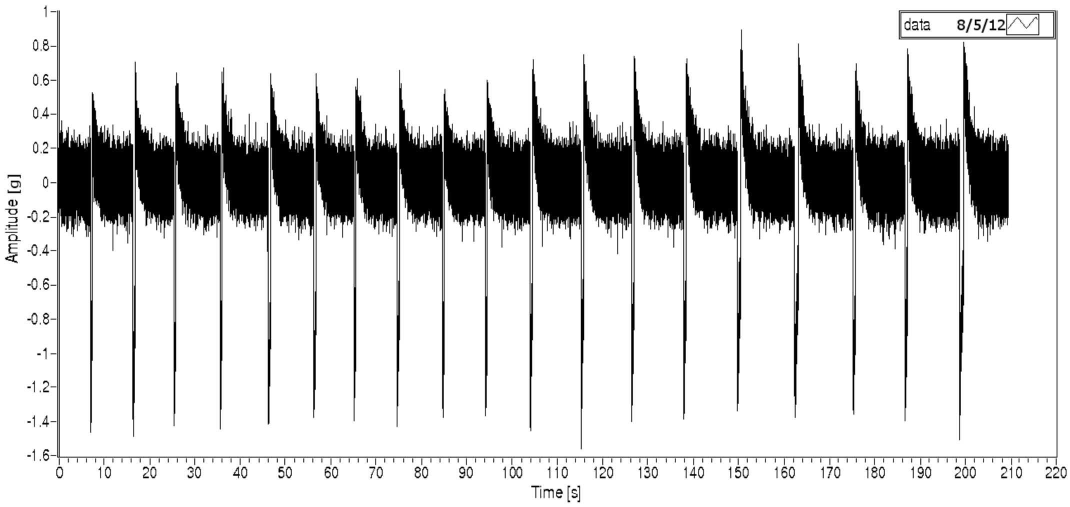


Figure 4.1.8: Vibration data acquired 8/5/2012

Since no information about changed working condition is provided and it is difficult to distinguish a "bad" measurement from the correct one before own processing, "bad" measurements are revealed until the extracted features are examined. The values of extracted features are usually out of standard range, hence the measurement can be consider as improper (See Section 3.3.1).

4.2 Working condition

As mentioned above, the measurement is carried out independently on the working condition. In Figures 4.1.1 and 4.1.3 is shown, that the speed range during measurement may be very variant. Further, in Figure 4.2.1, the average speed during particular measurements is displayed.

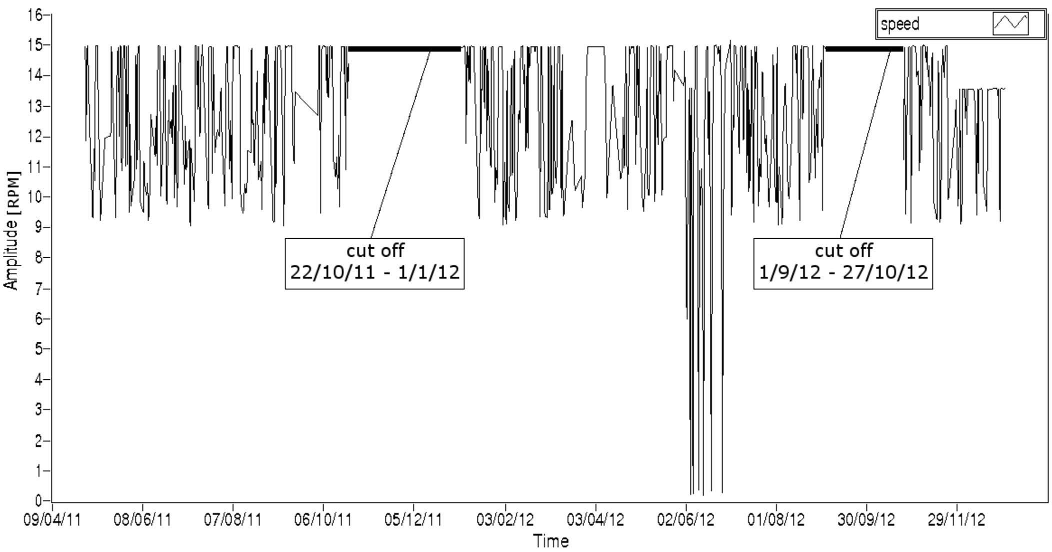


Figure 4.2.1: Average speed during measurements (2011-2012)

As mentioned in Sections 2.2.3.1 and 3.2, many features are dependant on working condition. Since the load is changing with speed, the values are also speed dependant. Hence, it is necessary to divide the measurements based on the speed behaviour. Therefore, two working classes were specified, as described in Table 4.2.1. The reason is explained as follows. In Figure 4.2.2, speed histogram is shown. It is clear that the usual working condition is between 9-15 RPM. Due to the speed dependence of extracted features, it would be suitable to create working classes with high resolution. However, a small number of samples was available, therefore only two working classes were defined, as shown in Table 4.2.1.

name	min avg. speed [RPM]	max avg. speed [RPM]	no. of samples
1	9	13	366
2	13	15	255

Table 4.2.1: Working classes

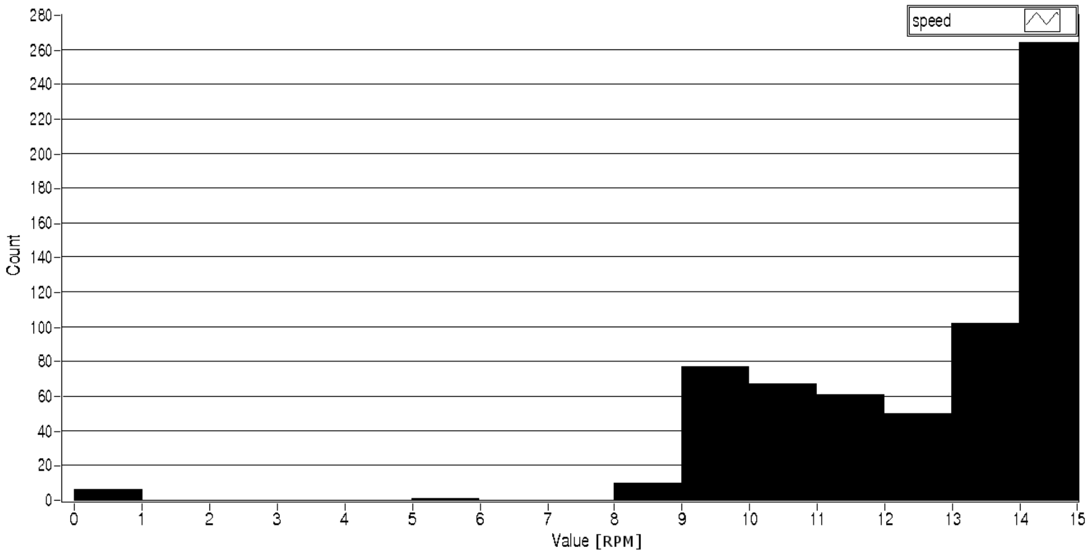


Figure 4.2.2: Histogram of average speed during measurements (2011-2012)

4.3 Trend examination

Figure 4.3.1 shows RMS values in full speed range. In comparison, Figures 4.3.2 and 4.3.3 show RMS values in the working class, defined in Table 4.2.1. It is clear, that the trend plot are more consistent in the conditioned cases. However, there are still random peaks. When the raw signal of corresponding measurement was examined, it was found that the waveform is similar to waveforms shown in Figures 4.1.4, 4.1.6, 4.1.8. Therefore, those peaks can be consider to be caused by "bad" measurement (See Section 4.1). Since the peaks are accidental, they can be removed by using median filter, which is described in Section 3.3.1.1. In Figures 4.3.4, 4.3.5, the smoothed RMS values are displayed. The median filter with left rank 5, right rank -1, was used.

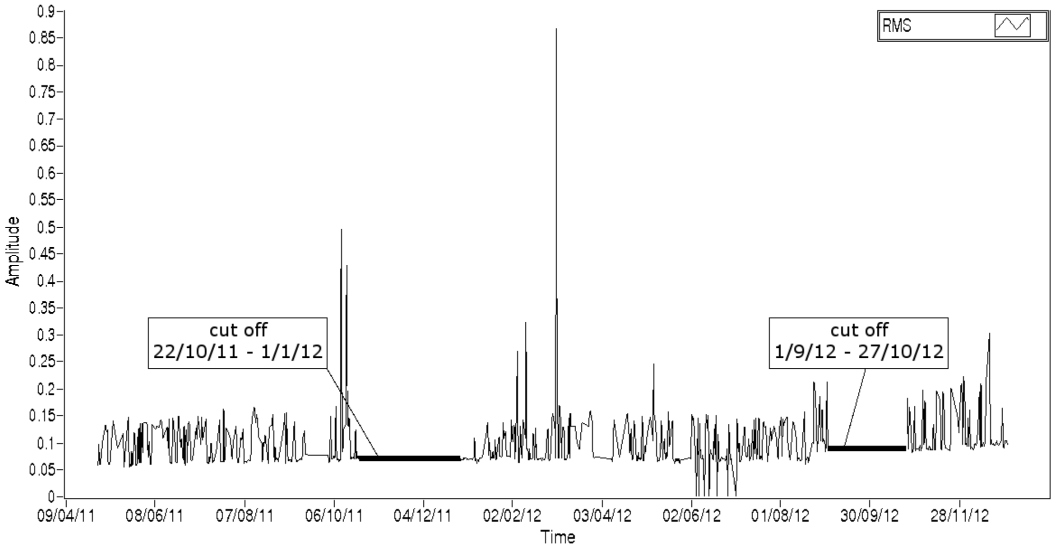


Figure 4.3.1: RMS values in full speed range (2011-2012)

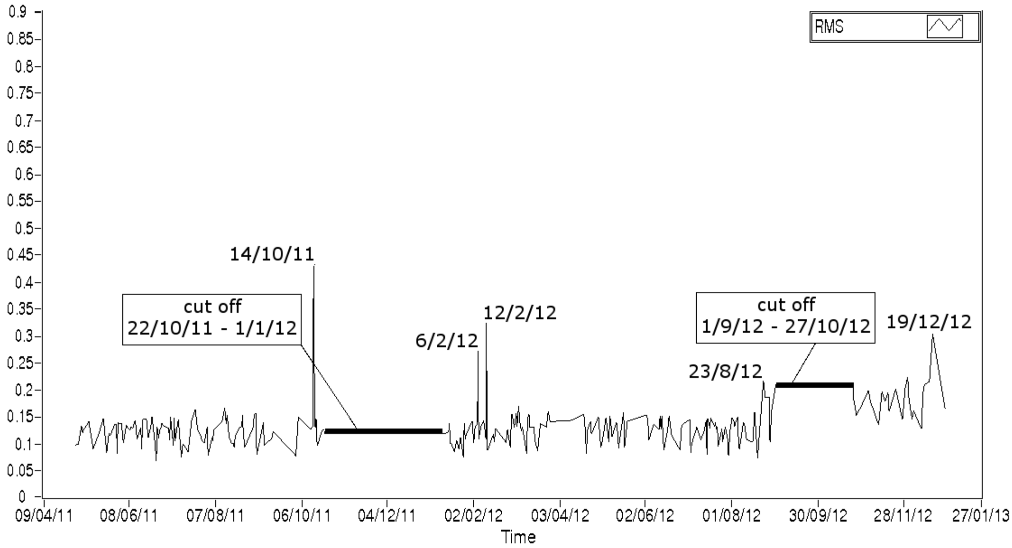


Figure 4.3.2: RMS - speed range 9-13 RPM (2011-2012)

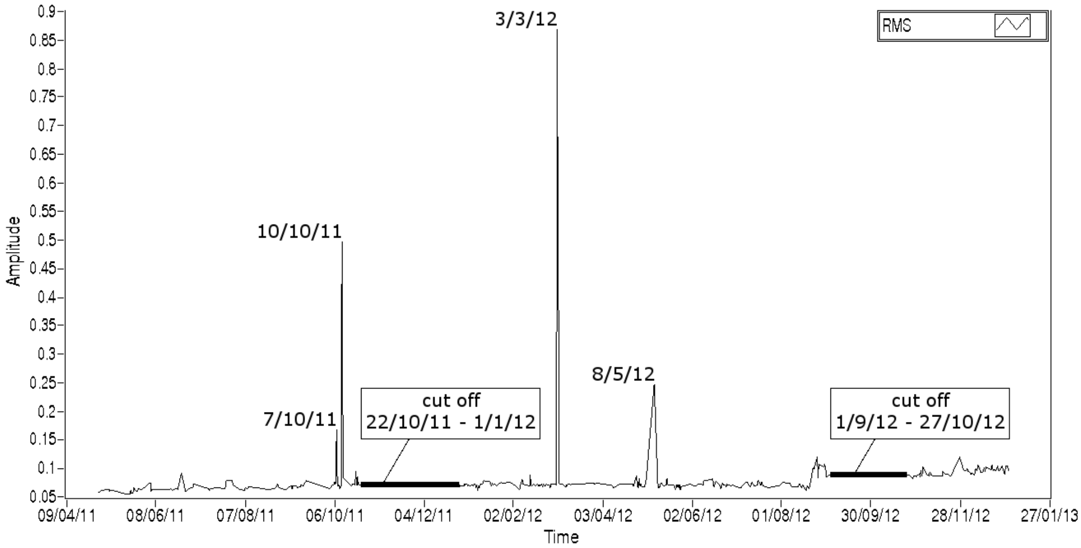


Figure 4.3.3: RMS - speed range 13-15 RPM (2011-2012)

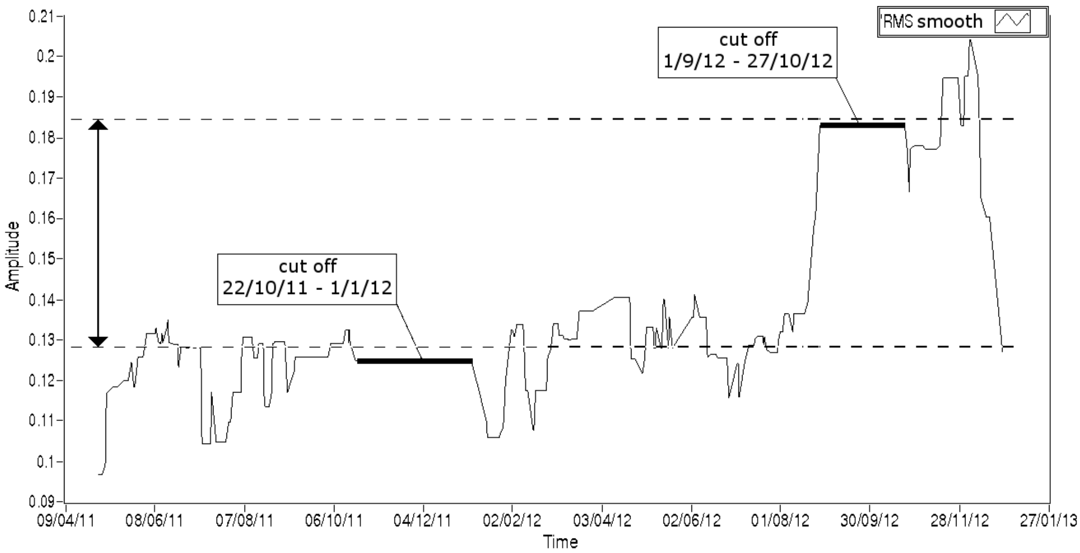


Figure 4.3.4: RMS smoothed - speed range 9-13 RPM (2011-2012)

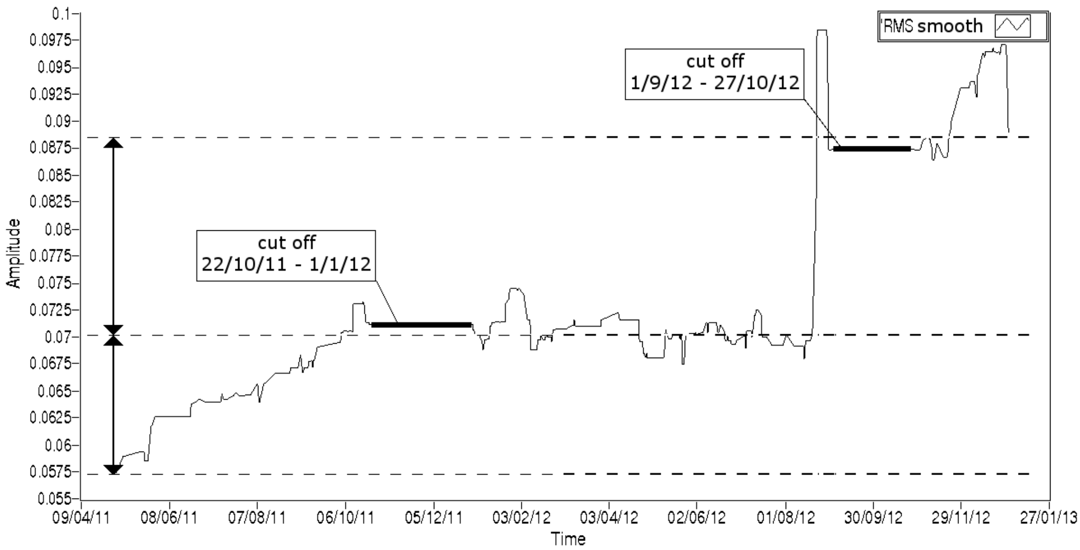


Figure 4.3.5: RMS smoothed - speed range 13-15 RPM (2011-2012)

When the data are conditioned by speed and smoothed, the change in the level can be clearly seen, as shown in Figures 4.3.4, 4.3.5.

4.4 Clustering

The aim of clustering methods is to group similar object (See Section 3.4.1). In case of this thesis, the clustering is based on trend analysis described in Section 4.3. In Figures 4.3.4, 4.3.5, the changes in the level of feature values are clear. This changes may be associated with two cut off events:

- 22/10/2011 - 1/1/2012,
- 1/9/2012 - 27/10/2012.

The three events split the whole examined time interval (2011-2012) into three time periods described in Table 4.4.1. In terms of the defined time periods, the data set was divided into three subsets based on the date of measurement.

cluster ID	start	end	description
0	1.1.2011	22.10.2011	before 1st cut off event
1	1.1.2012	1.9.2012	between cut off events
2	27.10.2012	31.12.2012	after 2nd cut off event

Table 4.4.1: Time periods

The clustering and subsequent classification procedures were applied to data of working class 13-15 RPM. The reason was that working class 13-15 RPM contains more samples and the changes in trend were more significant. Before, the clustering procedure started, 50 randomly chosen samples from the working class data set (training sets) were removed. Those samples will be used as unknown samples in classification procedure to verify the designed classifier.

Clustering results based on the time periods are displayed in Appendix C.0.1, where the axes of the graph are RMS and kurtosis. It can be seen that the orange points are out of main cluster. Some of the orange points is marked with the date of measurement. When the corresponding raw data were examined, it was found that the waveforms are similar to them displayed in Figures 4.1.4, 4.1.6, 4.1.8. Further, a small number of samples bounded with a dashed ellipse create another cluster outside the main one. It was found that these samples are characterized by very non-stationary speed during the measurement. An example of non-stationary speed during the measurement is shown in Figure 4.1.3. Due to the small number of points, it was decided that all points (orange) outside the main cluster make up only one another cluster. In the zoomed fraction of Figure C.0.1, it is clear that three clusters, based on the specification in Table 4.4.1, were formed. The results confirm the assumption that the maintenance during cut off events affected the resulting run of the wind turbine. Those clusters are clearly identified also in other 2D visualisations, not only when axes are RMS and kurtosis.
The covariance matrix and mean vector can be easily calculated for each of the four specified clusters. These matrices and vectors define corresponding

classes. After that, the points of the classes can be generated from Gaussian distribution (See Section 3.4.1.2) and the classes can be displayed, as shown in Figure C.0.2.

4.5 Feature reduction

In this section, the feature reduction is applied to the data set (See Section 3.3). The suggested correlation-based algorithm described in Section 3.3.3 was applied to the data set. The amount of information was decreased gradually and subsequently the algorithm reduced the dimension by removing the most correlated features. The results are provided in Table 4.5.1.

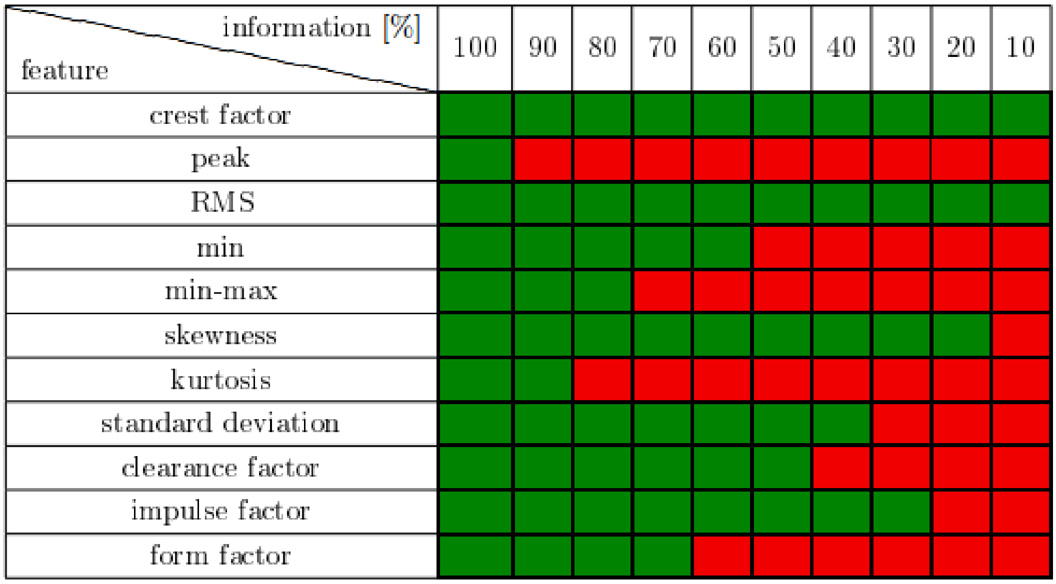


Figure 4.5.1: Feature reduction (red - removed)

In Table 4.5.1, it can be seen that the most informative features in case of the used data set were RMS and crest factor.

4.6 Classification

In this section, the pattern classification (See Section 3.4.1) will be applied to the data set. The aim of classification is to correctly classify new samples into defined classes. In case of this thesis, the classes were not defined a priori, therefore the classes were specified by clustering (unsupervised learning) in Section 4.4. The classes are described in in Table 4.6.1.

class ID	start	end	description
0	1.1.2011	22.10.2011	before 1st cut off event
1	1.1.2012	1.9.2012	between cut off events
2	27.10.2012	31.12.2012	after 2nd cut off event
3	—	—	"bad" measurement

Table 4.6.1: Classes

Before the clustering was carried out, the verification samples were removed from the data set. Thus, the classes were generated from a training set and after that, the classification was verified with unknown samples, which were not used in the training part.
The classification pattern contains following features (See Section 3.2.1):

- crest factor;
- peak;
- RMS;
- min;
- min-max;
- skewness;
- kurtosis;
- standard deviation;
- clearance factor;
- impulse factor;
- form factor.

No more features could be included into pattern vector due to the small number of samples, because the problem of overfitting may occur. It means that the number of samples in the training data set is not sufficient to the pattern dimension size and subsequent classification would fail.

The dimension and features of the pattern were chosen based on the feature reduction results, described in Table 4.5.1. The classification was carried out in four cases of feature reduction, namely when the amount of information was 100%, 70%, 40% and 10%.
During the feature reduction procedure described in Section 4.5, the covariance matrix and mean vector of each of the four classes were generated and stored. Then, the random samples of those classes could be generate by Gaussian distribution. These randomly generated points were used for classification verification. A new dataset of these samples were created, as shown in Table 4.6.2.

class	start sample	end sample
0	1	1000
1	1001	2000
2	2001	3000
3	3001	4000

Table 4.6.2: Generated data set

Then the classification was applied to this new dataset. The classification results for different pattern dimension size (amount of information) are graphically displayed in Appendix D.0.1. The evaluation of the classification results is provided in Table 4.6.3 and in Figure 4.6.1. It is clear, that the classification accuracy is decreasing when the pattern dimension size is reduced. However, it can be seen that when 70% of information was preserved, the classification results are always close to maximal accuracy. Moreover, when only 40% of information was preserved, the results are always very accurate.

information [%] / class	100	70	40	10
0	99.82	99.73	98.57	84.30
1	99.53	99.30	96.57	76.34
2	99.97	99.96	99.66	95.41
3	100.00	100.00	99.98	95.80

Table 4.6.3: Classification accuracy [%] - generated data

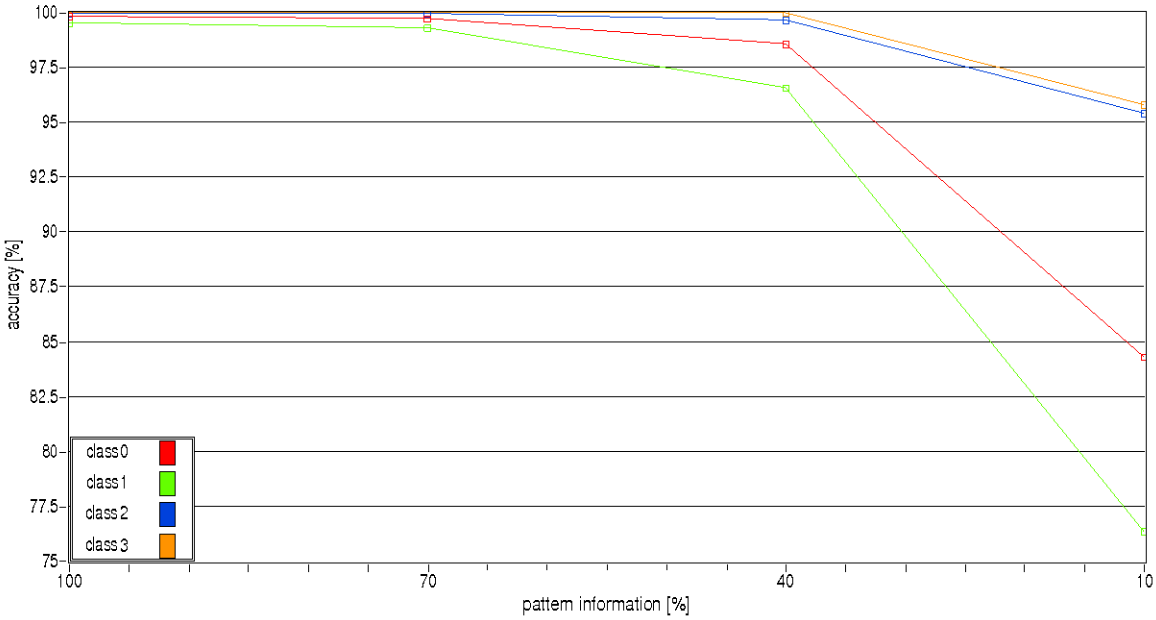


Figure 4.6.1: Classification accuracy - generated data

The same classification procedure were applied to a verification dataset of 50 real samples. The samples are displayed with classes in 2D space of RMS and kurtosis in Appendix D.0.3. The classification results are graphically displayed in Appendix D.0.2. It is clear again that the more features were removed from the pattern, the worse classification results were acquired. It can be seen, that some samples were incorrectly classified in all cases. The reason is that some samples are situated close to the boundaries of the class, as shown in Appendix D.0.3. In combination with class overlapping, the erroneous classification results may be obtained. Further, Appendix D.0.3 shows that two samples (marked with date) are out of main cluster. Both these samples were classified correctly in all cases. Nevertheless, the ambiguous results and the small number of samples caused that the final evaluation of classification accuracy cannot be provided.

5 LabView application

The implemented application can be divided into two parts:

Data processing of vibration signal and feature extraction;

Data analysis of extracted features over time.

In following section, the application is described and the user guide is provided. The illustrative figures of the application and its particular tabs can be found in Appendix E.

5.1 Data processing tab

Data processing tab deals with vibration data analysis. The tab contains four more sub-tabs:

- Processing setting;
- Time features;
- Spectrum;
- Log.

The main tab contains four control buttons to start, stop and pause data processing. Pause button makes sense when auto processing is running and the user wants to examine the current file without stopping the processing. The stop button in the right top corner ends the application. The application is equipped with control mechanism to prevent senseless setting and ensure correct results. Moreover, Descriptions and Tip options are also provided when right mouse button clicks on an object of interest.

Processing setting tab

This tab enables to adjust the processing setting to the requirements of the user. At first,the operational mode must be specified:

Manual
: Only one tdms file is processed. Its location is specified in data path box.

Auto
: All tdms files in a folder are processed one by one. The location of the folder is specified in data path box.

The application expects steady structure of tdms file. When the user wants to save the extracted features, the feature file location must be specified.

On the right side of the tab, the user can specify the preprocessing and processing setting:

Data filtering
: Setting of the IRR filter. The high pass filter is default option because time domain vibration features require filtering the DC component.

Data conditioning
: The user can specify the offset and gain to compensate calibration error.

Integration
: Signal integration can be used to change the vibration type (acceleration, velocity, displacement).

Spectrum setting
: The configuration of spectrum computation can be adjusted. When the checkbox auto is checked, the maximal order is determined from feature processing setting on the left side, otherwise the maximal order is select automatically. When order resolution is set to zero, the

maximal available resolution is used. See Section 3.2.2.1, where these options and its relations are described.

On the left side of the tab, the user can specify the features to extract:

Vibration features such as crest factor, RMS, etc. (See Section 3.2.1).

Frequency component in orders (See Section 3.2.2.2). The names of components and frequencies must be saved in external txt files (component.txt, frequency.txt).

Envelope extraction setting is enabled.

When more then one channel are processed, the user can specify more channel settings. It is assumed, that the names of data files starts with the channel number such as 00, 01, ... 15. Then the corresponding setting can be used. When only one feature extraction setting is entered, is can be used for all channels.
Finally, the user can save its setting to the xml file and use it in next session.

Time features tab

This tab provides the visualisation of the loaded vibration data. User can display the speed data, loaded vibration data and also the preprocessed and envelope data which were acquired with preprocessing operations. The requested time domain features are also displayed.

Spectrum tab

This tab enables spectrum analysis of preprocessed signal and its envelope. The spectra are displayed and they can be saved in tdms file and loaded in next session. The requested spectral components are also displayed.

Log tab

This tab provides information about the processing. When auto processing is running, a warning can occur because some files may contains unusable data. The table on the right side contains information about the loaded spectra on the previous tab.

Data analysis tab

This tab provides a tool to examine the extracted features and analyse the potentiality of fault detection.
At first, the user must specify the path to the tdms file with extracted features. When the file is loaded, the user can select the features to analyse. When the user requires conditioning by speed, the speed channel must be specified. When the time-axis is required with values, the timestamp channel must be also specified. When working classes are specified on the Setting tab, the user can select one to condition the data. When the user requires removing of random peaks, the smoothing must be set (See Section 3.3.1).

Trend tab

This tab enables to examine trends of selected features within the selected working class.

Statistic tab

This tab displays the histograms of selected features within the selected working class.

Correlation tab

This tab displays the correlation matrix of selected features within the selected working class. The Correlation sum list displays the sum of correlations for particular features and the box Information specifies the setting for feature reduction method (See Section 3.3.3.1).

Clustering tab

This tab provides a tool to realise pattern classification (See Section 3.4.1). When features are selected and feature reduction is done (or not), the user can observe the n-dimensional space via a 2D window, whose axis can be selected by user.

Clustering mode is activated with the corresponding button and it can be done manually or with K-mean algorithm (See Section sec:kmean). The recommended way is to use K-mean and then the suggested clusters can be modified manually. The number of clusters can be changed at will during clustering process. The number of the edited cluster is selected in box Cluster. Clear button deletes actual selection. Double click on this button deletes all marks.

Time analysis of particular measurements can be performed when the checkbox Date is checked. The radio button enable to select the long or short date format.

Classes can be displayed, when clustering is finished by pressing button Done. Then the corresponding representation of particular classes is generated and the classes can be plotted by pressing button Plot class.

Class analysis tab

This tab shows the representation of selected clusters, namely its covariance matrix and mean value (See Section 3.4.1). The representation can be saved and loaded in next session.

Classification tab

When classes are created during clustering or loaded from previous work, the classification can be performed. The box Classes enables to select the classes which will participate in the classification process. The chart displays the classification results graphically (See Section 3.4.1.2).

Setting tab

This tab enables to create particular working classes.

6 Conclusion

Fault diagnostic is of prime importance for the safe and effective operation of mechanical systems. In case of wind power plants, the pressure to quality is especially high due to enormous installation investment and high costs of maintenance. The most common technology of condition monitoring is vibration-based diagnostic, which can reveal change in vibration behaviour associated with the wind turbine drive train failure. Subsequently, the results from vibration diagnostic must be analysed by an expert system to assess the current health condition and generate recommendation or eventually an alarm. Due to the regular condition monitoring and assessment, the maintenance can be scheduled reasonably and the costs are reduced.

In this thesis, the meaning of condition-based monitoring is introduced and the structure of monitoring system is described based on the common ISO standards. Further, the most common failures and their symptoms are described together with the vibration methods used to feature extraction. Subsequently, the feature reduction meaning is introduced and suitable algorithm is suggested. Finally, the clustering and pattern classification is presented as s potential method for fault detection.

In practical part, the introduced methods were applied to experimental data. At first, the row data were analysed and it was shown that the measured data may contain erroneous samples, which may effect consequent processing, and therefore it should be take into consideration. Then, the values of features were analysed over time and two cut off events were identified. It was assumed, without any a priori information, that the cut off events may signify fault occurrence. Therefore, the measurements were divided into three groups based on the date of measurement. When the features were displayed in more dimensional space (2D), corresponding clusters were formed. It acknowledged the assumption that measurements during similar operational condition fall within same cluster,which can be distinguished from clusters formed by different conditions.

The statistical representation, namely covariance matrix and mean vector, was computed class based on the identified clusters. After that, new samples of particular classes could be generated by using Gaussian distribution. These samples was used to verify the obtained classifier and evaluate the feature reduction method. It was confirmed that when the number of features, which create the pattern, was reduced too much, the classification generates more erroneous results. Nevertheless, till the amount of information in left features was above certain level, the classification results were acceptable, no matter how many features were removed.

In term of future work, the positive contribution of feature reduction to classification results must be confirmed by applying it to higher number of real samples, which was not available in case of this work. The training data set should contain longer time history and the information about the fault events must be provided to associate particular samples and clusters with real operational conditions. Furthermore, more sophisticated feature extraction method should be examined to provide more informative features. Namely, phase analysis may enable to distinguish different faults on rotating parts and methods in time-frequency domain may provide new information, which cannot be obtain in frequency or time domain.

In conclusion, the thesis realize the defined aim which was to summarize the rotating machine faults and suggest a way to realize fault detection. In additional, the requirements of the submitter from Areva GmbH to implement an application in LabView, by which the measurement data can be examined, was accomplished.

Appendices

Appendix A

M5000 datasheet

M5000-116

General

Rated power	5,000 kW
Cut-in wind speed	4 m/s
Rated wind speed	12,5 m/s
Cut-out wind speed	25 m/s
Design life time	20 years
Type class	GL-TK 1 offshore

Rotor

Rotor diameter	116 m
Number of blades	3
Swept rotor area	10,568 m²
Rated speed	14.8 min^{-1}
Rotor axis tilt angle	5°
Cone angle	–2°

Pitch system

Principle	electrical pitch
Power control	blade angle and rotor speed control

Tower

Type	tubular steel tower

Gearbox

Type	step-planetary gear, helical
Ratio	1:10

Generator and Converter

Generator type	synchronous, permanentmagnet
Rated voltage	3,300 V
Speed range	45.1 – 148.5 min^{-1}
Cooling	water cooled
Protection class	IP 54
Converter type	full size converter
Power factor (grid)	0.9 inductive – 0.9 capacitive

Masses

Hub incl. Blades	110 t
Total top mass	345 t

M5000-135

General

Rated power	5,000 kW
Cut-in wind speed	3.5 m/s
Rated wind speed	11.4 m/s
Cut-out wind speed	25 m/s
Design life time	20 years
Type class	GL-TK 1 & GL-TK S

Rotor

Rotor diameter	135 m
Number of blades	3
Swept rotor area	14,326 m²
Rated speed	13.5 min^{-1}
Rotor axis tilt angle	5°
Cone angle	–3,5°

Pitch system

Principle	electrical pitch
Power control	blade angle and rotor speed control

Tower

Type	tubular steel tower

Gearbox

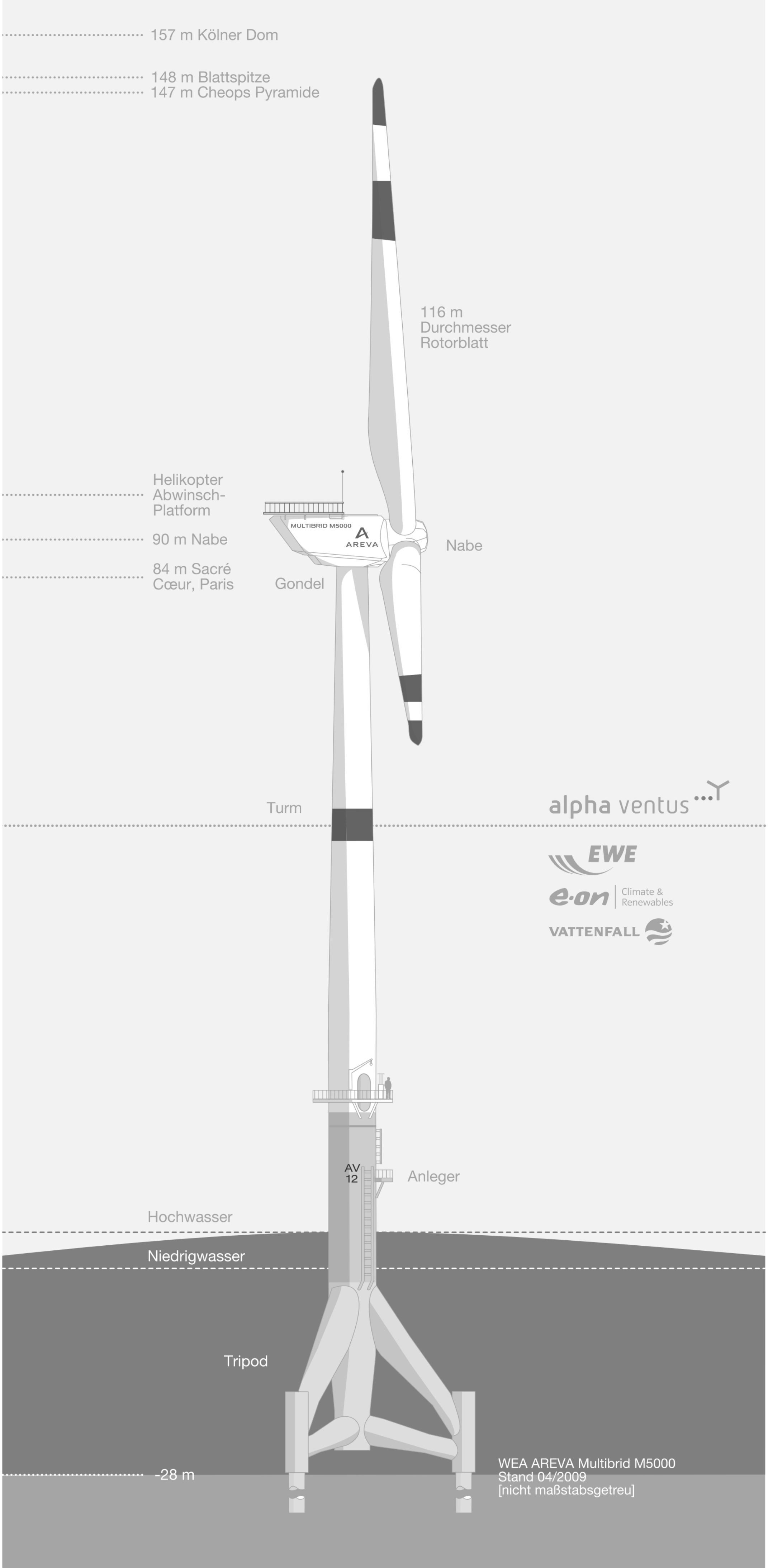
Type	step-planetary gear, helical
Ratio	1:10

Generator and Converter

Generator type	synchronous, permanentmagnet
Rated voltage	3,300 V
Speed range	66.1 – 133.5 min^{-1} ± 10%
Cooling	water cooled
Protection class	IP 54
Converter type	full size converter
Power factor (grid)	0.9 inductive – 0.9 capacitive

Masses

Hub incl. Blades	140 t
Total top mass	375 t



157 m Kölner Dom
148 m Blattspitze
147 m Cheops Pyramide
116 m
Durchmesser
Rotorblatt
Helikopter
Abwinsch-
Platform
90 m Nabe
84 m Sacré
Cœur, Paris
MULTIBRID M5000
AREVA
Nabe
Gondel
Turm
alpha ventus
EWE
e·on
Climate &
Renewables
VATTENFALL
AV
12
Anleger
Hochwasser
Niedrigwasser
Tripod
-28 m
WEA AREVA Multibrid M5000
Stand 04/2009
[nicht maßstabsgetreu]

Appendix B

WinDrive

Clever Combination of Speeds.
How the WinDrive Functions

Two main components of the WinDrive are the technique behind how it functions: a planetary gear combined with a hydrodynamic torque converter.

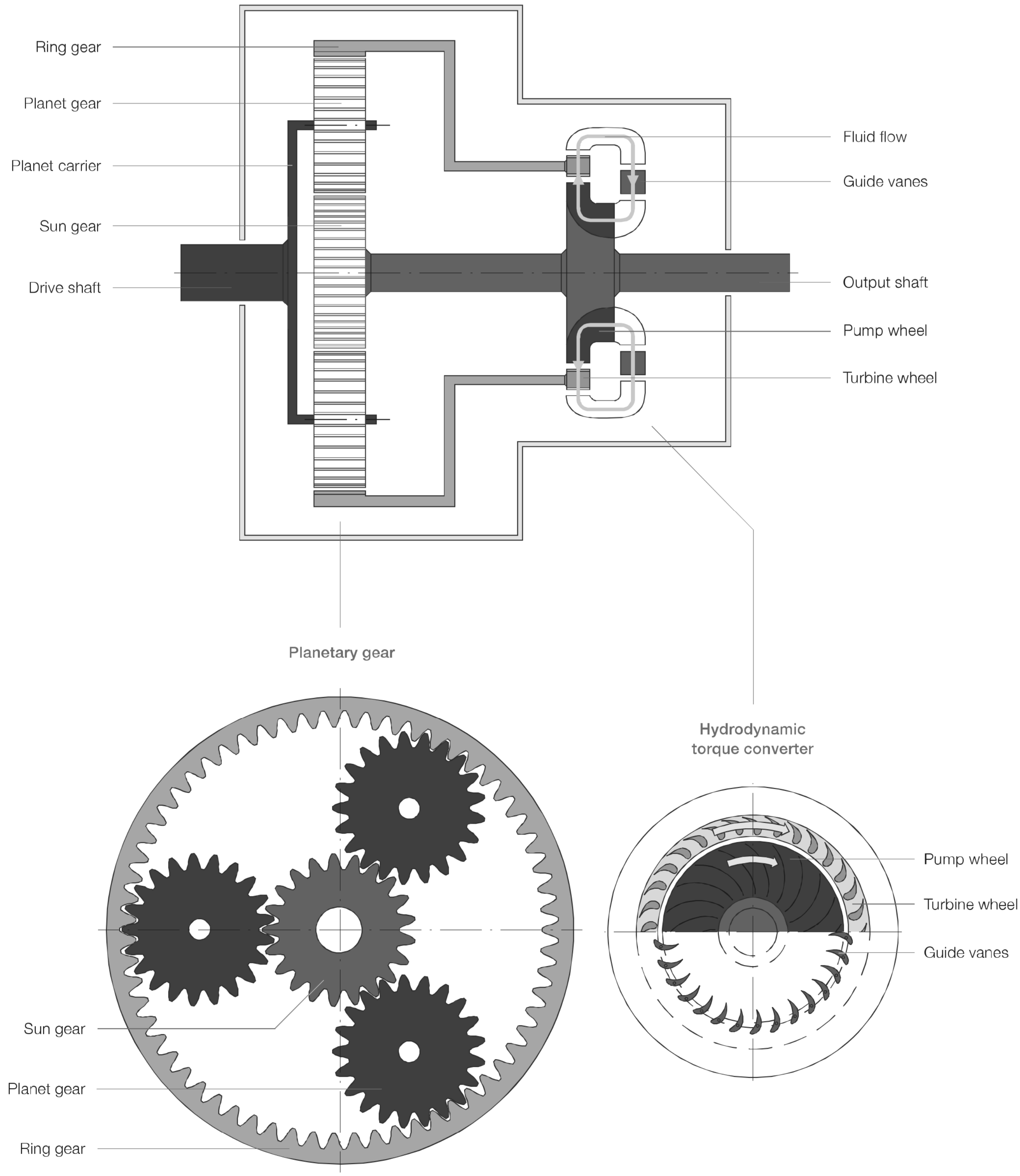
Design

- The WinDrive is placed in the driveline of the wind turbine between the main gearbox and the generator.
- The planetary gear consists of the sun gear, the planet gears and the ring gear. The planet gears are mounted on the rotating planet carrier.
- The torque converter consists of three main components: pump wheel, turbine wheel and adjustable guide vanes. A sealed housing filled with hydraulic fluid holds these components.
- The pump wheel is connected to the output shaft of the WinDrive. The turbine wheel is connected to the ring gear of the planetary gear.

How it functions

- The wind rotor drives the planet carrier via the main gearbox. The planet gears drive the sun gear.
- The sun gear drives the generator and the pump wheel of the torque converter via the output shaft.
- The pump wheel accelerates the hydraulic operating fluid, which in turn drives the turbine wheel. The operating fluid flows back into the pump wheel through the adjustable guide vanes.
- Power transmission in the torque converter is wear-free. The position of the guide vanes determines the amount of power transmitted.
- The WinDrive transmits the major portion of the power directly from the wind rotor to the generator. The torque converter diverts only a small fraction of the overall power. This diverted power is fed back to the planetary gear through the ring gear.
- The planetary gear combines the power from the wind rotor with the adjustable power fed back through the ring gear to then drive the sun gear at a constant speed. The generator speed is therefore, also held constant.

Basic design of the WinDrive



Appendix C

Clustering

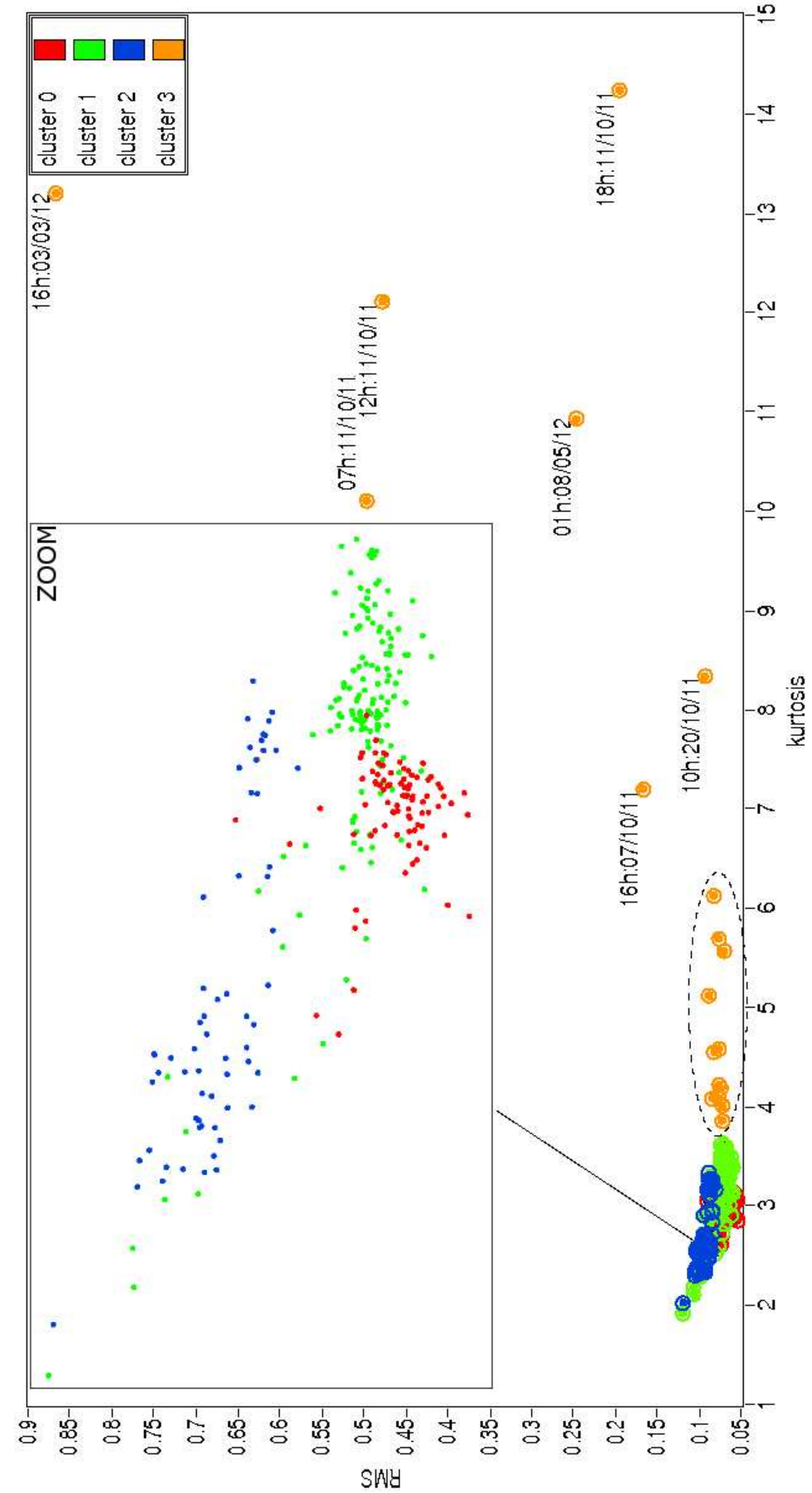


Figure C.0.1: RMS, kurtosis in speed range 12-15 RPM (2011-2012)

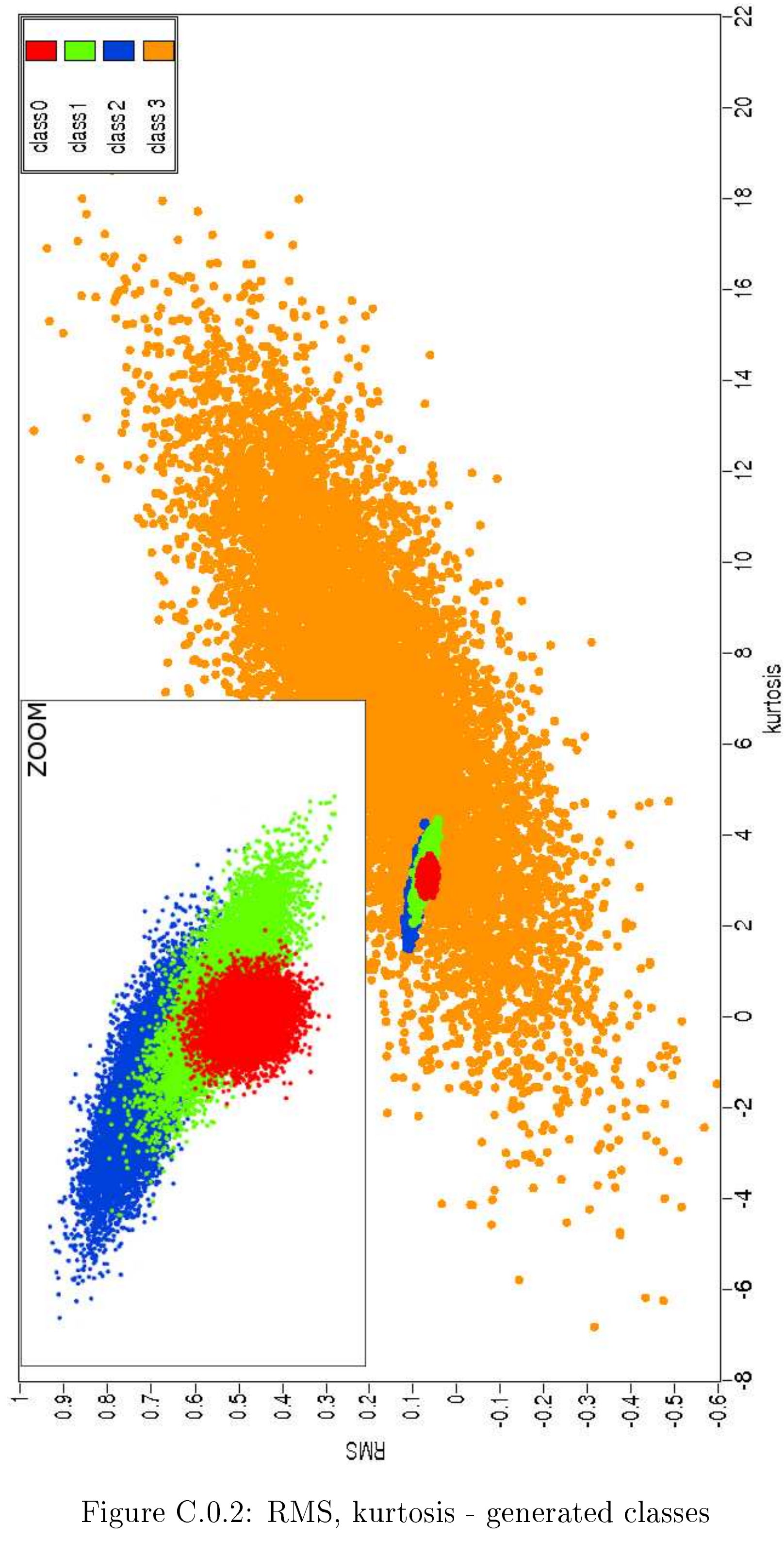


Figure C.0.2: RMS, kurtosis - generated classes

Appendix D

Classification

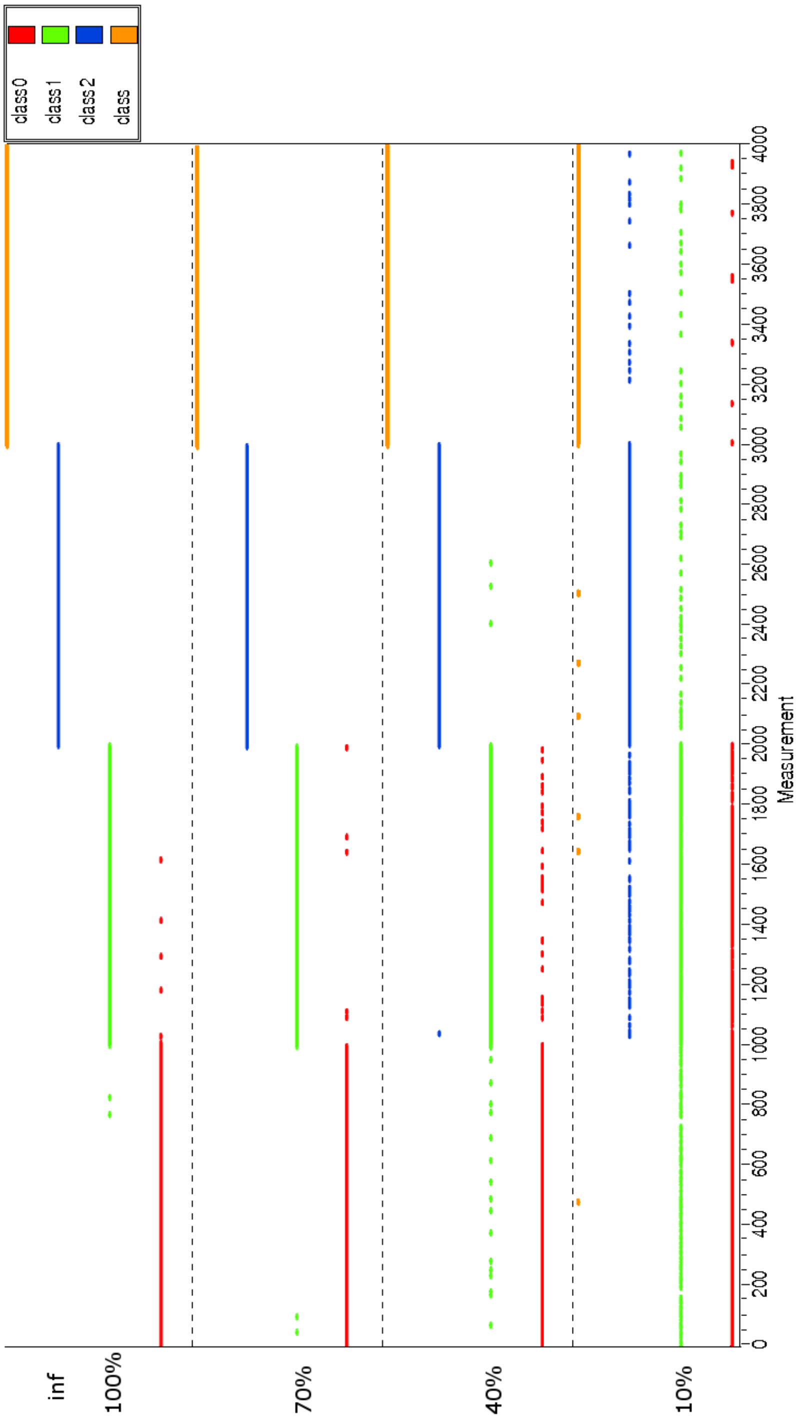


Figure D.0.1: Classification results - generated data

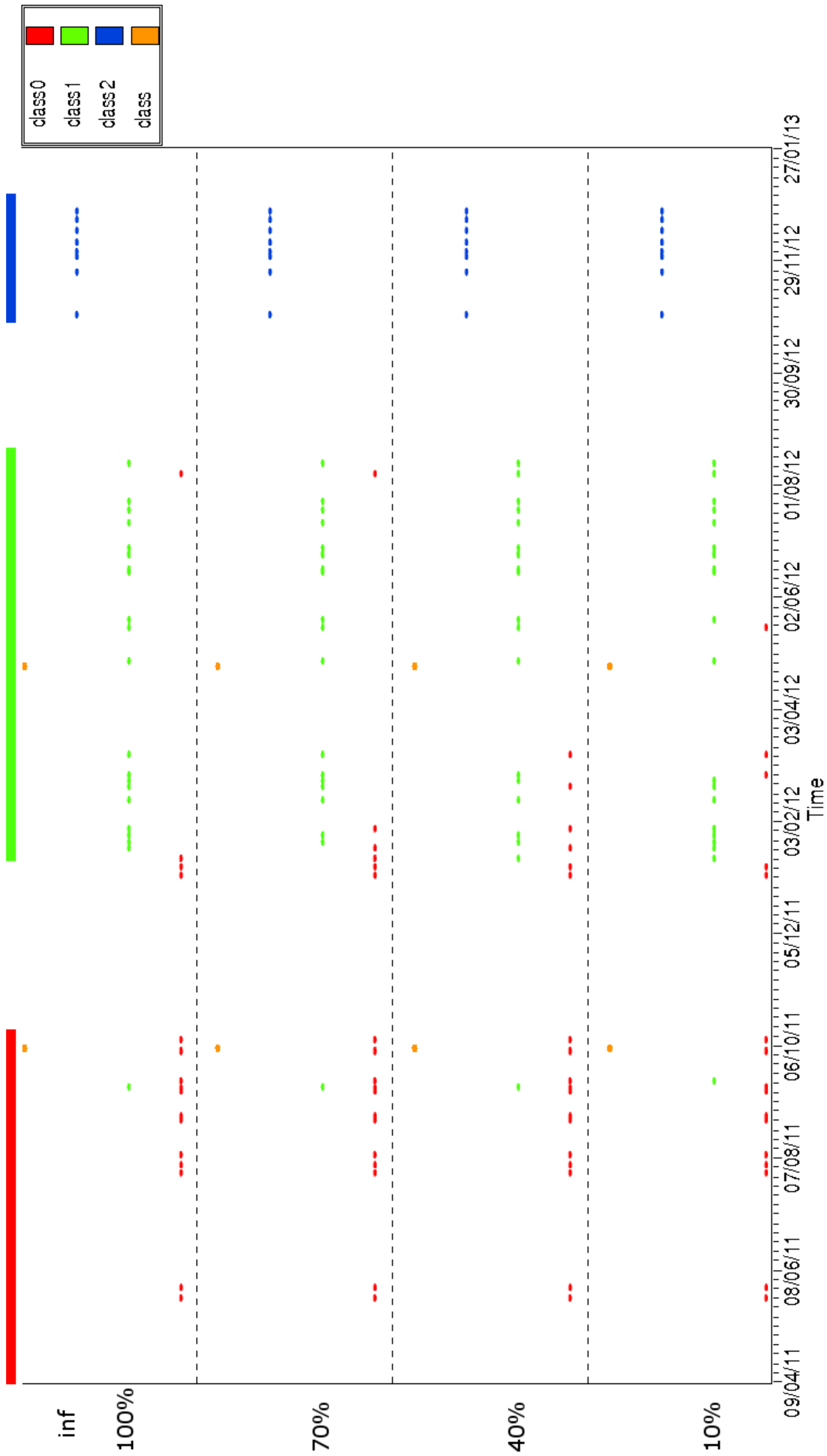


Figure D.0.2: Classification results - real data

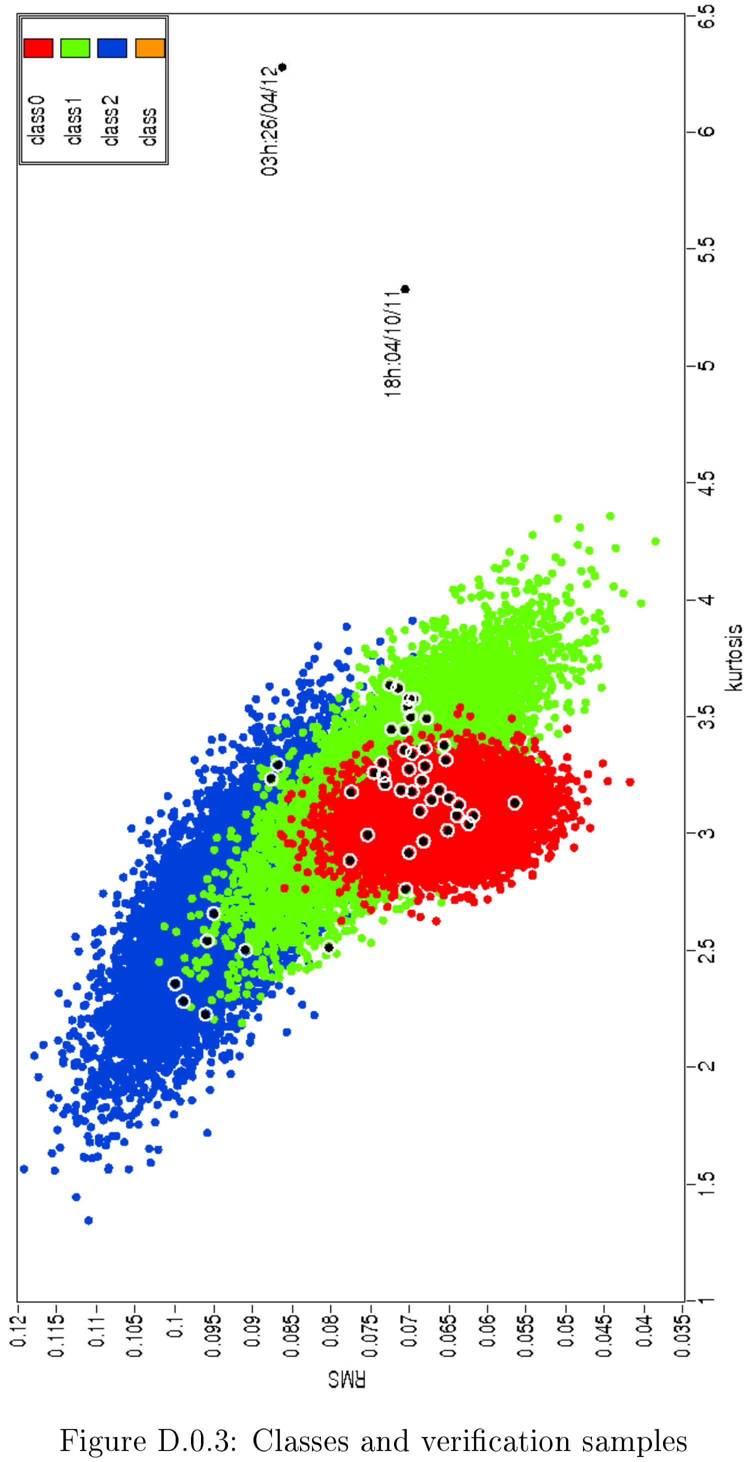
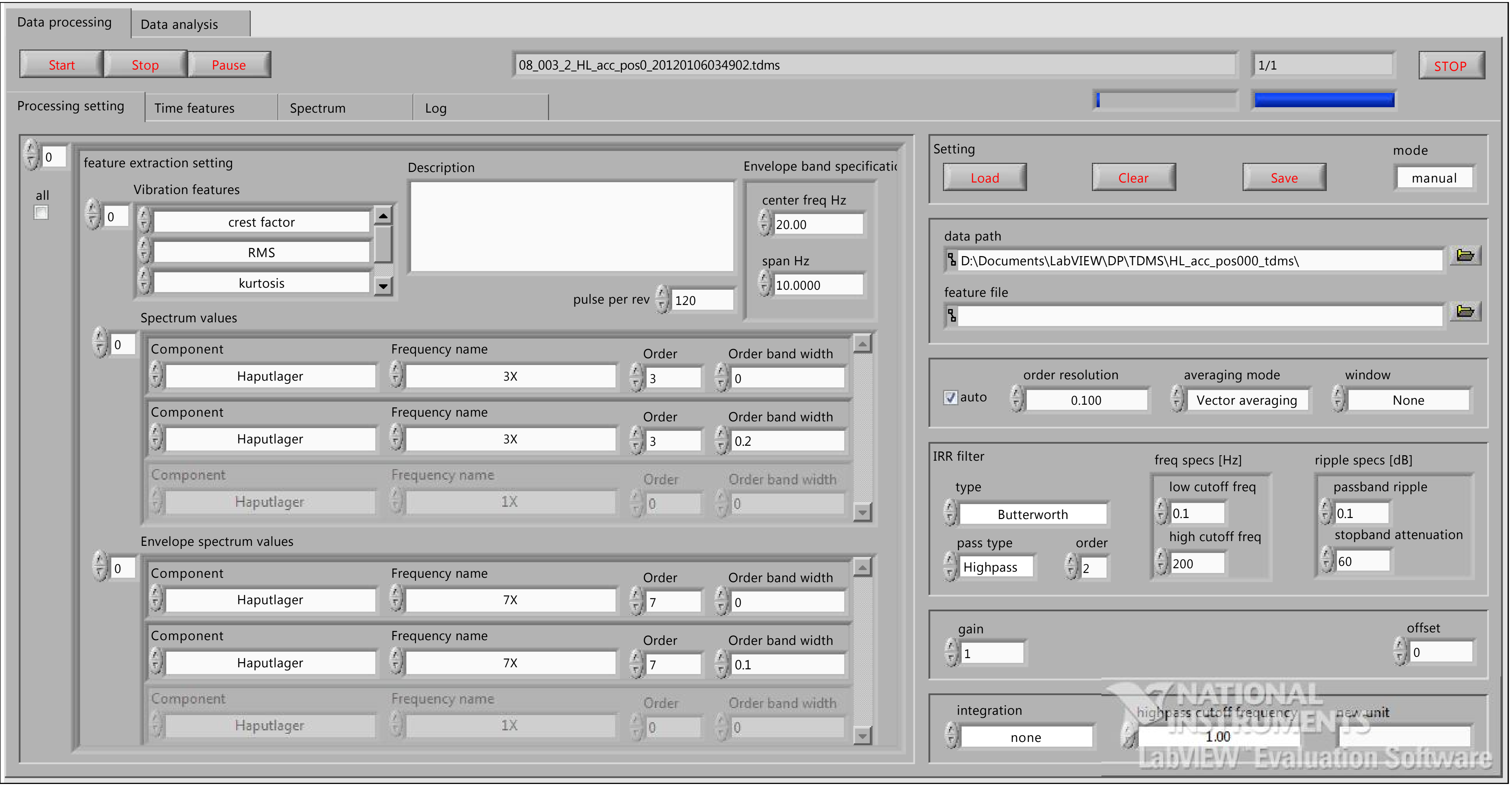


Figure D.0.3: Classes and verification samples

Appendix E

LabView application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Order band width
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Envelope spectrum values
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Component
Haputlager
Frequency name
7X
Order
7
Order band width
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Component
Haputlager
Frequency name
7X
Order
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200
ripple specs [dB]
passband ripple
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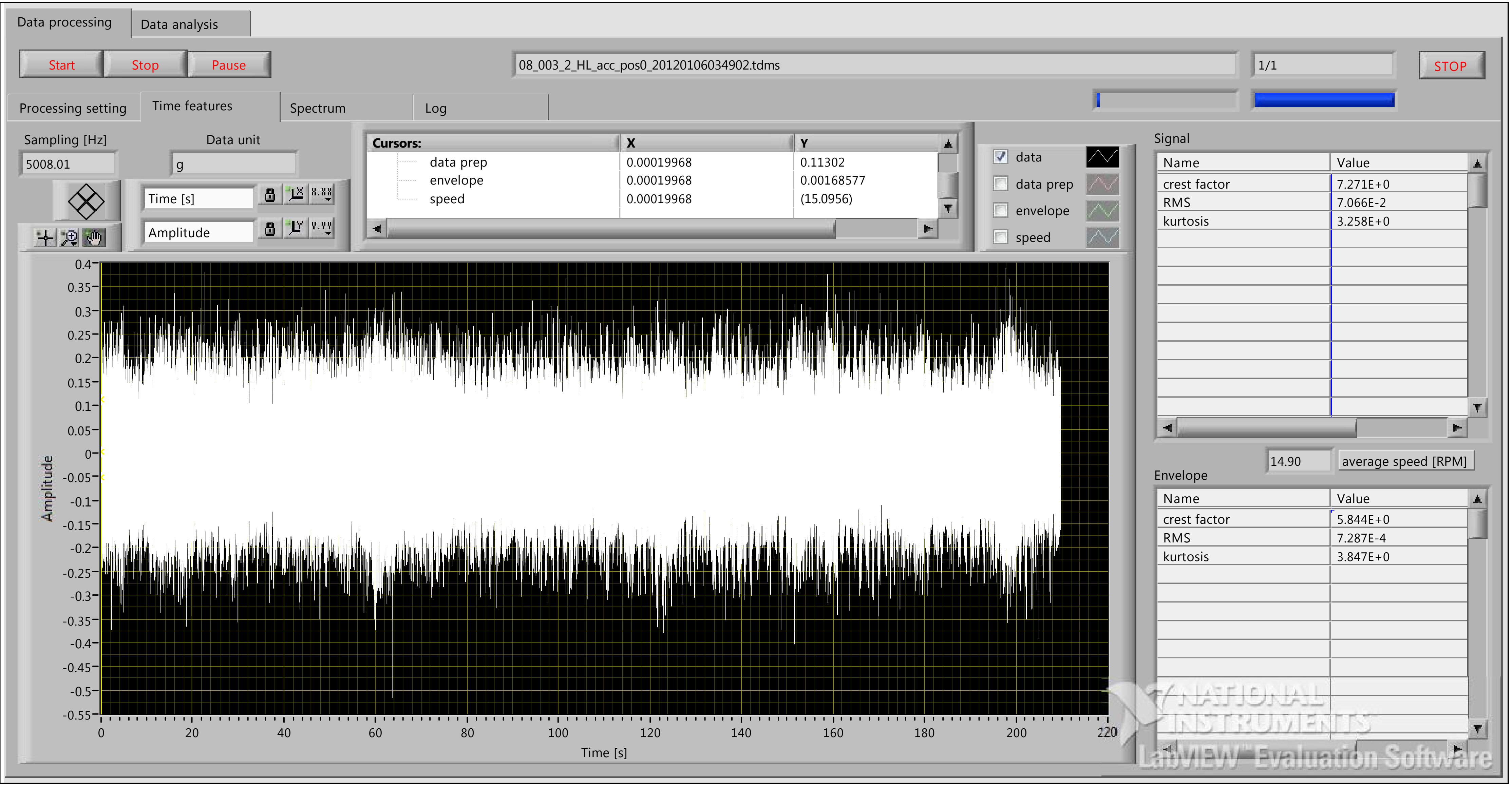
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average speed [RPM]
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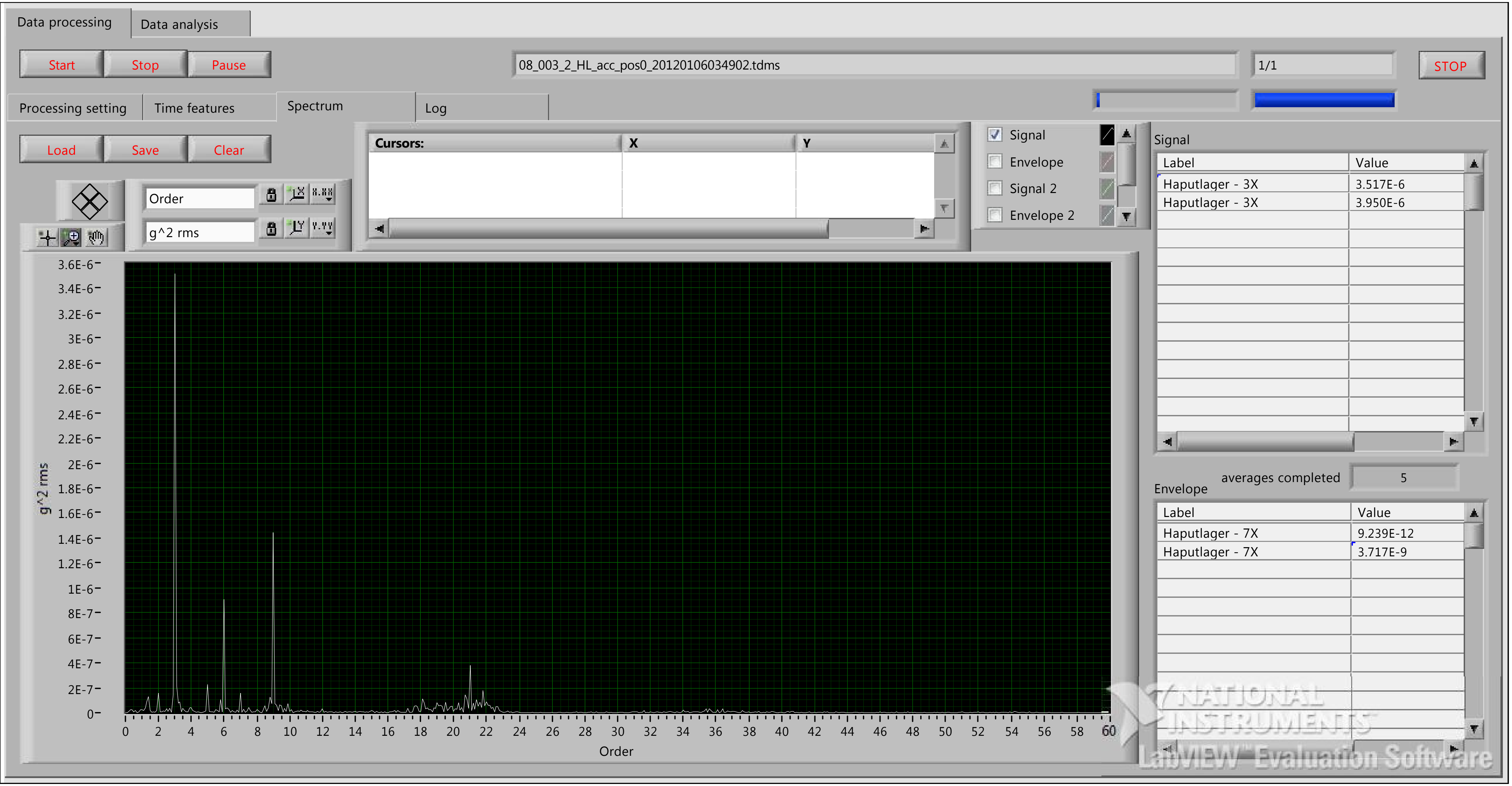

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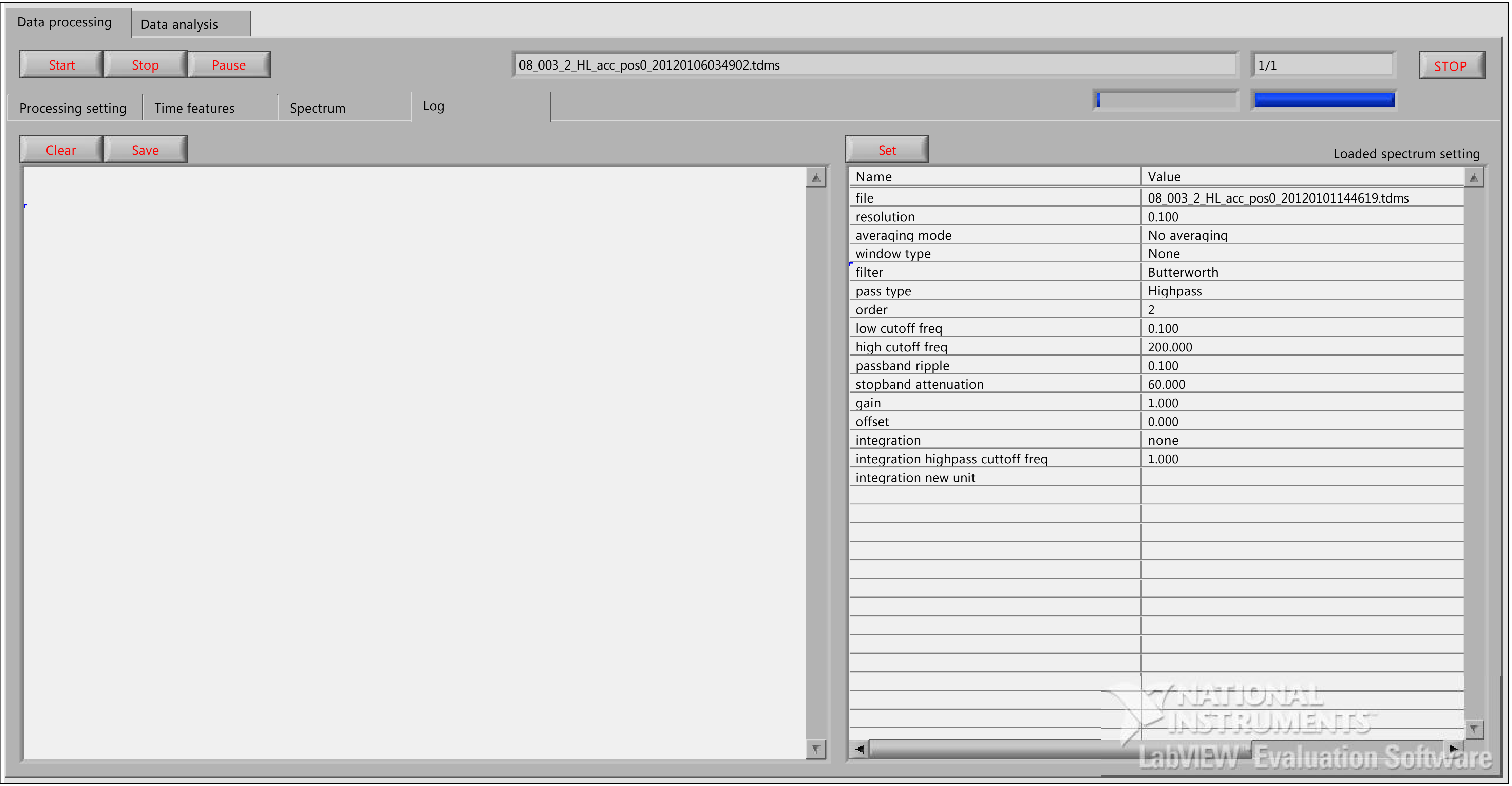
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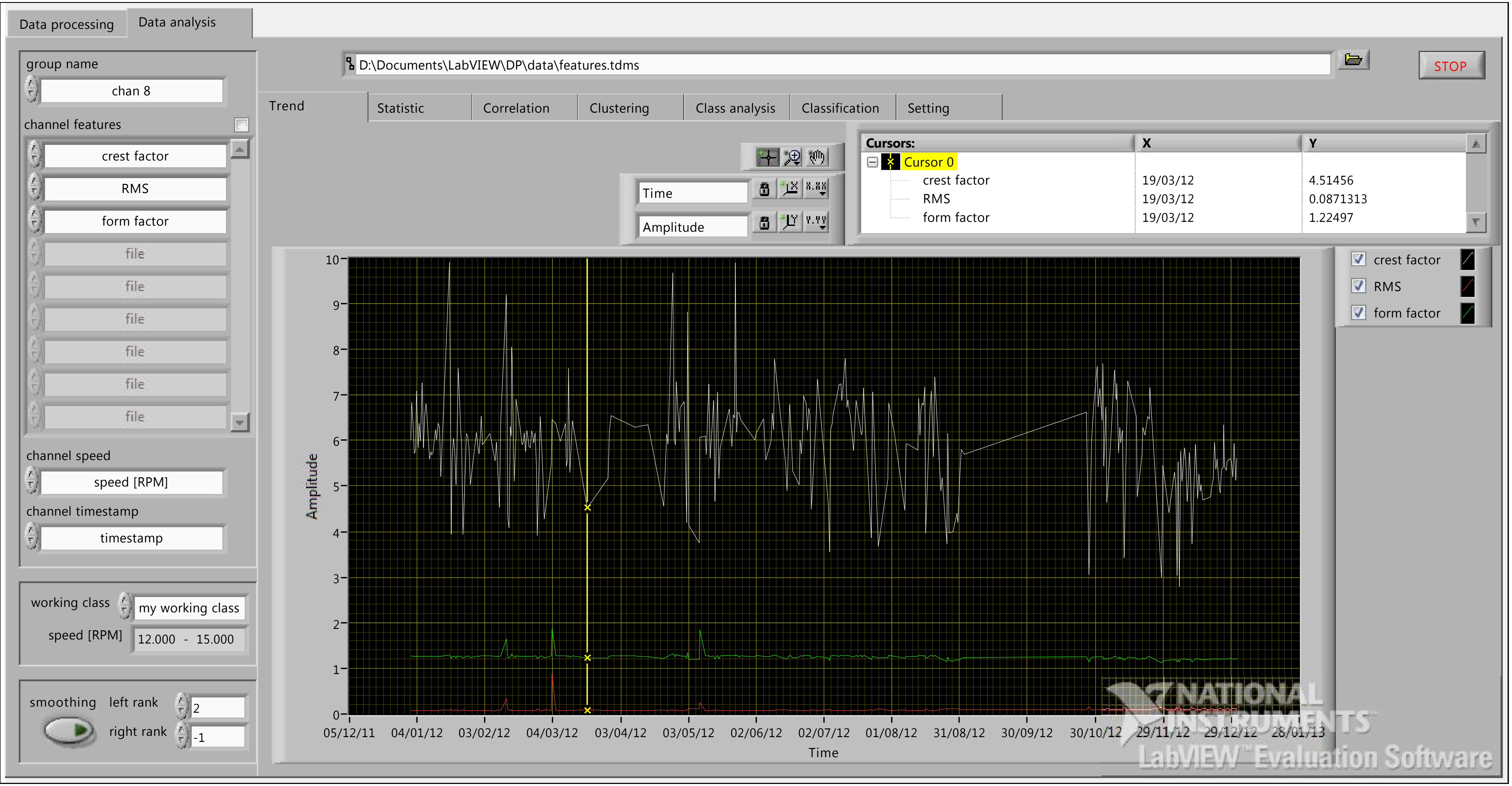

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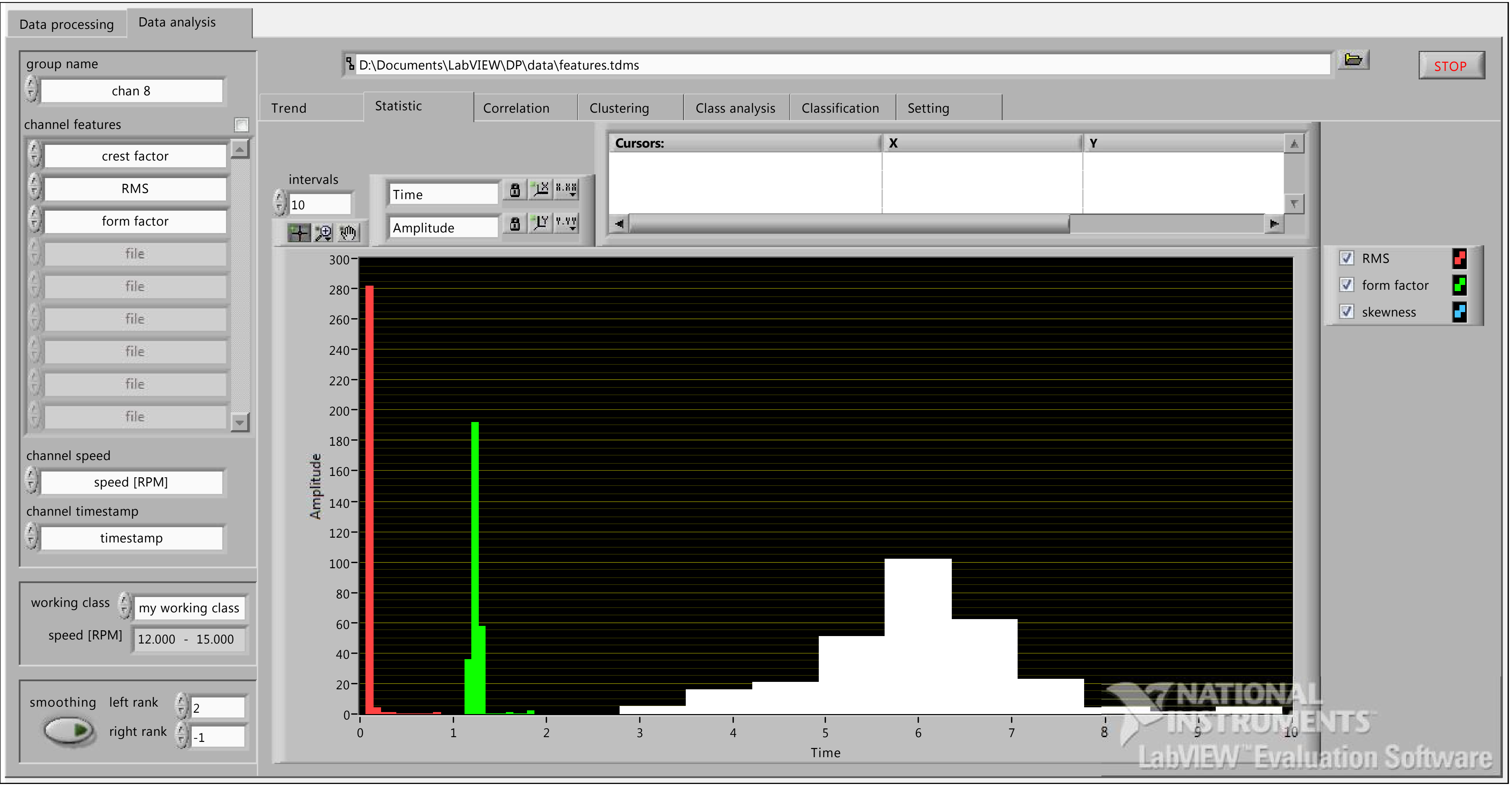

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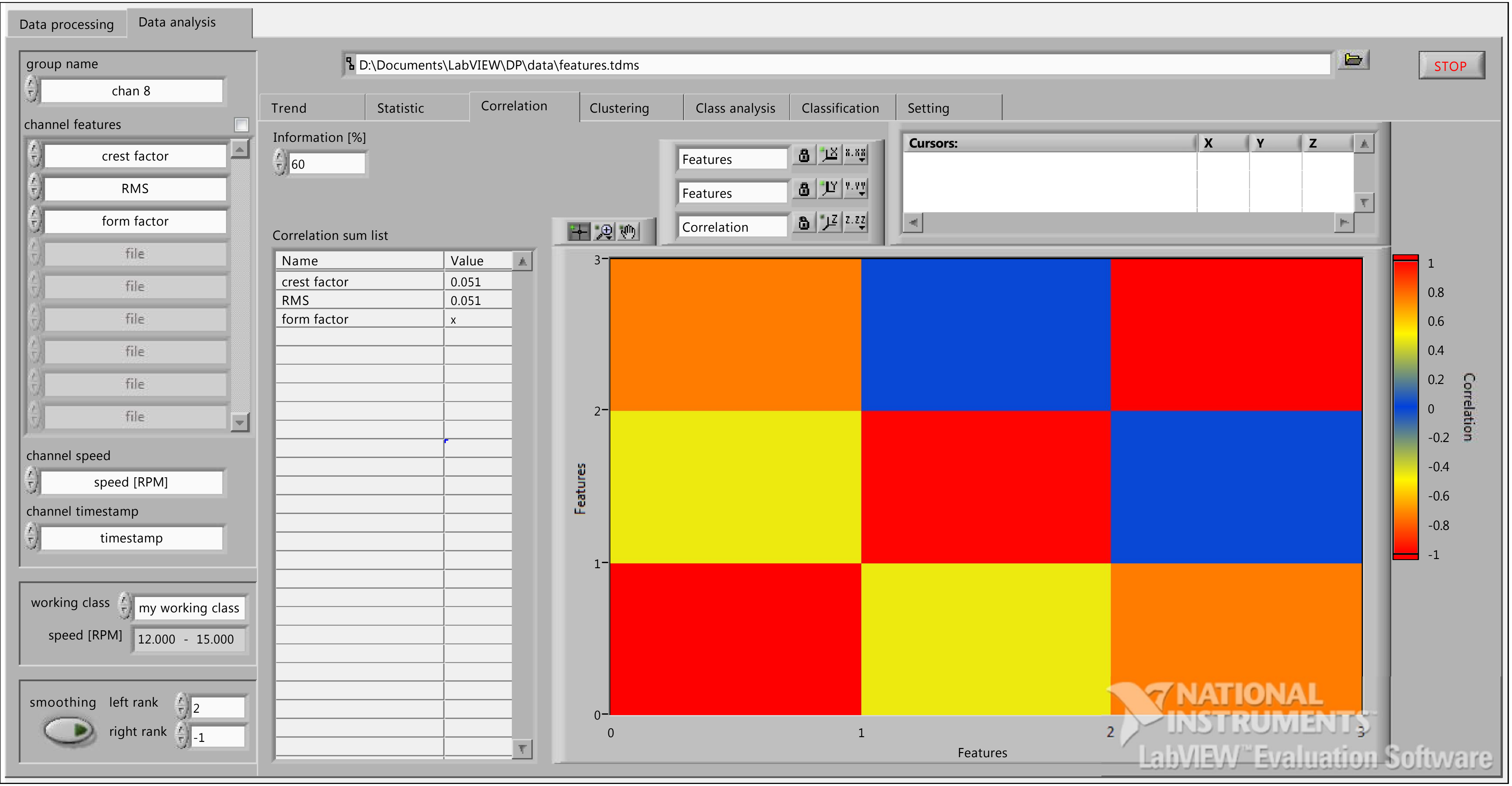

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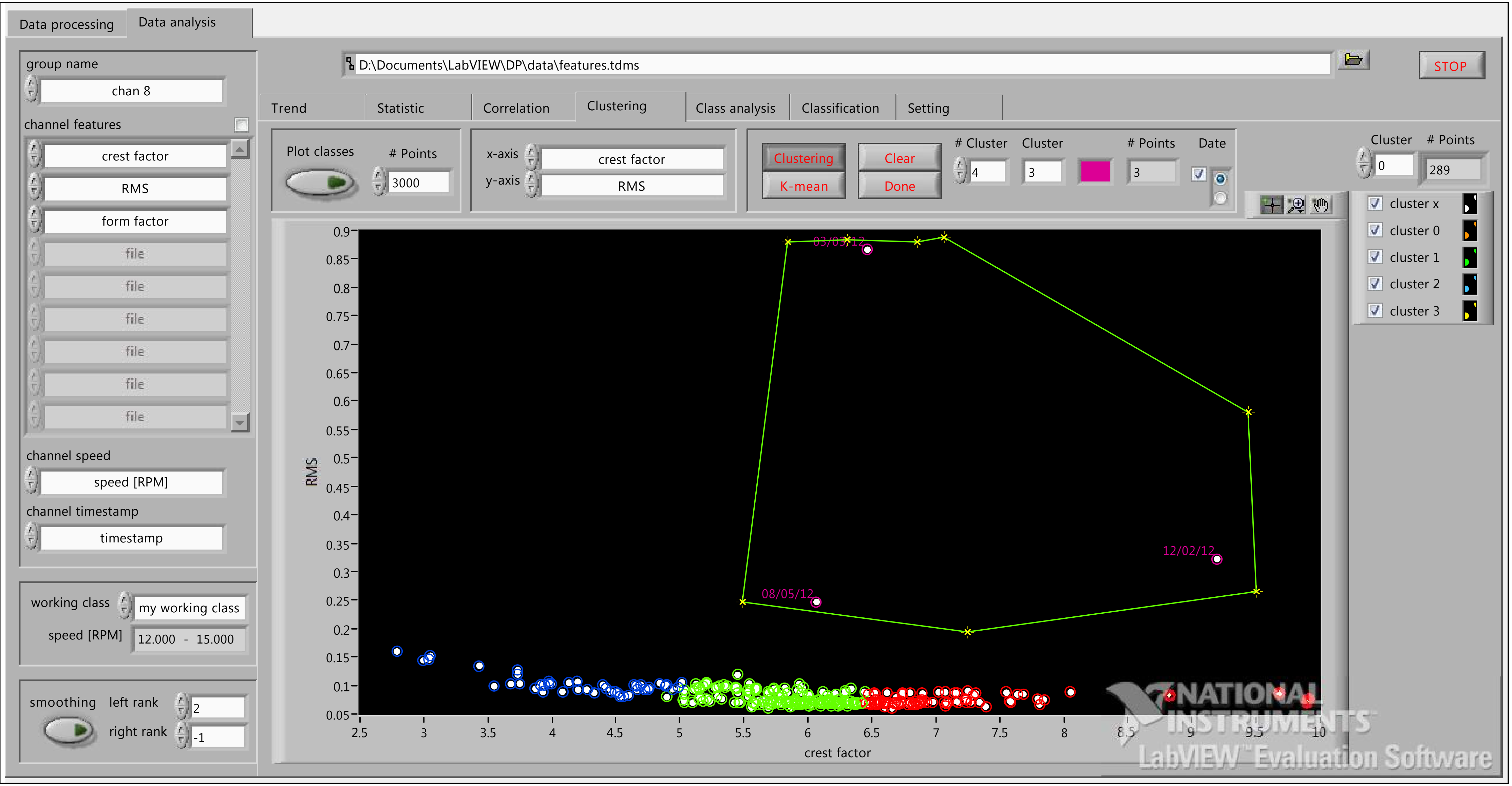

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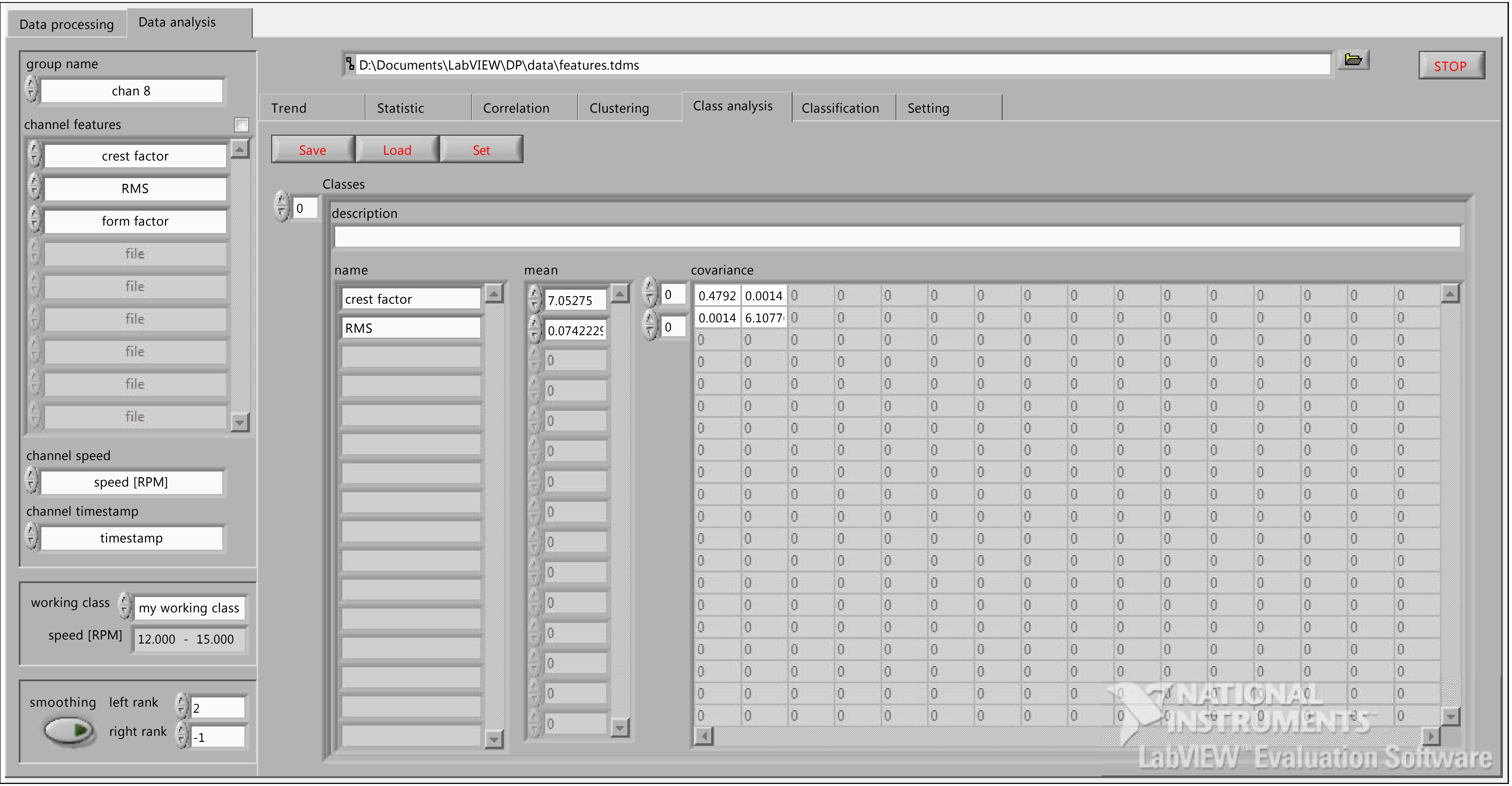

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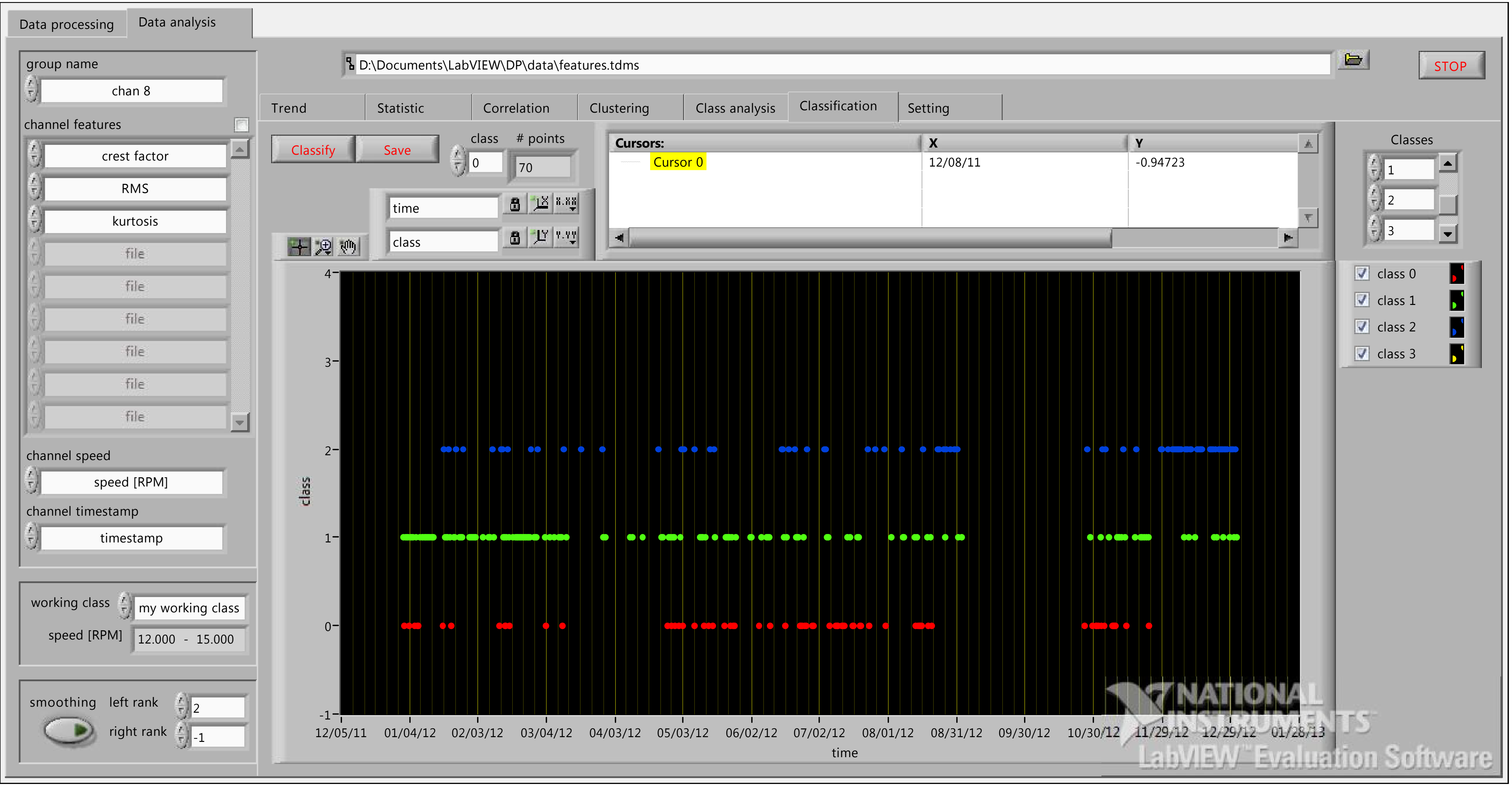

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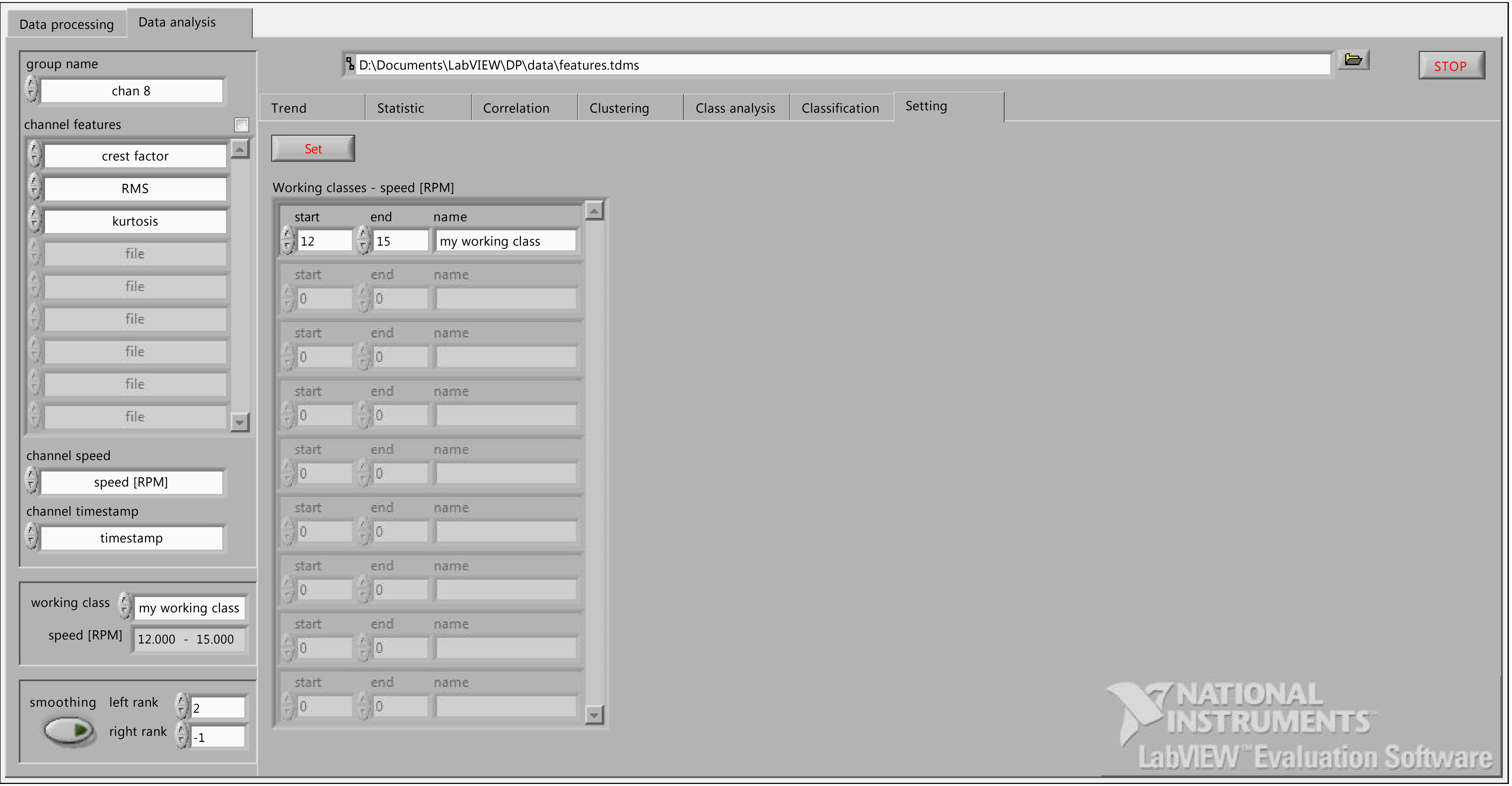
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Class analysis
Classification
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NATIONAL INSTRUMENTS
LabVIEW Evaluation Software

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